Hometown Lending

Ivan Lim and Duc Duy Nguyen*

*Ivan Lim (ivan.lim@durham.ac.uk) is at Durham University Business School, Durham University, Mill Hill Lane Durham DH1 3LB, UK; Phone: +44(0) 191 33 45200. Duc Duy Nguyen (duc_duy.nguyen@kcl.ac.uk) is at King's Business School, King's College London, 30 Aldwych, London WC2B 4BG; Phone: + 44(0) 113 34 38805. We are grateful to Paul Malatesta (the Editor) and an anonymous referee for very helpful comments and suggestions. We also thank Seth Armitage, Thorsten Beck, John Beshears, Zhong Chen, Kai Choy, Colin Clubb, Cláudia Custódio, Jo Danbolt, Bob DeYoung, Tarik Driouchi, Angela Gallo, Niklas Gawehn, Angelica Gonzalez, Paul Guest, Jens Hagendorff, Niels Hermes (discussant), Tom Hough, Elizabeth Kiser (discussant), Zicheng Lei, Tobias Meyll (discussant), Tony Moore, Maurizio Murgia, Linh Nguyen, Trang Nguyen, Dimitris Petmezas, Ben Sila, Raymond So, Wei Song, Simone Varotto, John Wilson, Bin Xu, Chao Yin, Yeqin Zeng, and participants at the 2019 FMA European Conference in Glasgow, the 2018 St Louis Fed Community Banking Conference in St Louis, the 2018 Social Finance and Financial Technology conference in Edinburgh, the 2018 EFMA conference in Milan, and seminar participants at the Free University of Bozen-Bolzano, King's College London, and the Universities of East Anglia, Reading, Surrey, and Swansea for various helpful comments. The usual disclaimer applies.

Abstract

Banks open more branches and make more lending near their Chief Executive Officers' (CEOs) childhood hometowns. The effects are stronger among informationally opaque borrowers and among CEOs who spend more time in their childhood hometowns. Furthermore, loans originated near CEOs' hometowns contain more soft information and have lower ex-post default rates, implying that hometown loans are more informed. Hometown lending does not affect aggregate bank outcomes, suggesting that credit is being reallocated from regions located farther away to regions proximate to bank CEOs' hometowns.

JEL Classification: G2, G21, G3

Keywords: home bias, CEOs, banks, lending, information

I. Introduction

Individuals tend to gravitate toward places of familiarity (Proshansky (1978)), and this can influence their behavior, and ultimately, performance outcomes. For instance, mutual fund managers invest more in stocks headquartered in the states in which they grew up (Pool, Stoffman, and Yonker (2012)), credit analysts rate issuers in their home states more generously (Cornaggia, Cornaggia, and Israelsen (2020)), and corporate managers are more likely to spare workers near their childhood homes from industry distress (Yonker (2017a)). Building on this literature, we focus on the childhood hometowns of CEOs[1] and examine whether bank CEOs are home biased when they shape the bank's branching and lending decisions. This is an economically important question, not least because bank credit is a key input to the economy.

Bank CEOs may implement policies to open more branches and extend more loans near their hometowns for two main reasons. First, the effects could be driven by advantages CEOs have in their hometowns. One possible advantage is information.[2] Information access constitutes one of the most fundamental forces in shaping lending transactions (Petersen and Rajan (2002)). Banks often devote significant resources to collecting information, particularly qualitative ("soft") information such as opinions, rumors, or economic projections, in order to gain a strategic advantage in ensuing transactions (Liberti and Petersen (2019)). A hometown advantage could

[1] Following the prior literature, we define CEOs' childhood hometowns as the counties in which they were born. As we also know the location of the CEO's current workplace (i.e., the bank's headquarters), this allows us to isolate hometown from workplace effects.

[2] There is a large body of literature showing that locals benefit from an information advantage. For instance, Bae, Stulz, and Tan (2008) and Malloy (2005) show that local analysts make more accurate forecasts. Coval and Moskowitz (1999) find that mutual fund managers are more likely to hold shares of local firms and earn significant abnormal returns from these investments.

allow CEOs to obtain superior inside information at a lower cost from their family or contacts who still live in the area. CEOs could therefore exploit this advantage to open more branches in their hometown areas, thereby facilitating expansions in local lending (Nguyen (2019)).[3] Other than CEOs themselves possessing superior information, hometown advantages could also manifest in the CEO's ability to manage local employees. For instance, CEOs could be better able to identify and hire skilled local branch managers. Relatedly, hometown commonality also allows CEOs to have more effective interactions with and a better understanding of employees in their hometown areas (Duchin and Sosyura (2013)).[4] This could empower local employees and incentivize them to exert more effort in collecting and utilizing borrower soft information in order to make more informed lending decisions (cf. Skrastins and Vig (2019)).

Second, CEO hometown lending could be driven by agency conflicts between CEOs and shareholders (e.g., Jensen and Meckling (1976), Shleifer and Vishny (1997)). According to this explanation, CEOs use hometown lending as a means of extracting rents from shareholders (Kruger (2015), Masulis and Reza (2015)). By actively implementing favorable branching and lending schemes in their hometowns, CEOs could accrue various private economic benefits, such as local awards, directorships, and speaking engagements, or they could gain an elevated status within the local community (Jiang, Qian, and Yonker (2019)). CEOs could also gain non-economic

[3] For instance, CEOs may have access to certain information (such as there will be a large factory opening in their hometown area) that would create new employment opportunities and boost local incomes. The CEO may decide to act upon this information and implement policies to open more branches and encourage local officers to lend more in that area.

[4] Duchin and Sosyura (2013) argue that social connections between a firm's CEO and its divisional managers can foster mutual trust, which reduces organizational hierarchy and motivates divisional managers to make more informed capital budgeting decisions (cf. Cross and Parker (2004)).

utility from hometown lending. For instance, CEOs may favor their hometown because they are emotionally attached to the place where they were born and raised. Psychologists argue that place attachment can form a key element of an individual's personal identity (Proshansky (1978)) and motivate them to invest time and money in the welfare of residents in their place of attachment (e.g., Manzo and Perkins (2006), Vaske and Kobrin (2001)).[5]

Importantly, the two explanations offer different empirical predictions concerning loan performance. If the hometown lending effects are driven by CEOs' superior information or superior ability to hire and empower local employees (Duchin and Sosyura (2013)), hometown loans should be optimal. That is, loans originated near CEOs' hometowns should have lower default rates and contain more soft information compared to distant loans. In contrast, if hometown lending is driven by agency motivations, then hometown loans should perform worse. We also recognize that these explanations can be at work simultaneously. We therefore examine which explanation is likely to dominate on average by tracking ex-post loan performance.

We begin our analysis by examining whether banks have differential branching and mortgage lending policies near their CEOs' hometown areas. We hand-collect data on the birth counties of 485 U.S.-born CEOs of publicly listed banks from 1999 to 2014. Of the 485 CEOs, 314 (65%) work for banks headquartered in the same state as their birth states, suggesting that many banks prefer hiring local CEOs to expand their regional business activities. To isolate CEOs' hometown lending from their banks' regional focus, we focus our analysis on 171 non-local CEOs

[5] In line with this, Yonker (2017a) finds that CEOs are more likely to spare workers in their childhood homes from the consequences of industry distress and that the effect is more salient among firms with weak governance. This suggests that the decision is likely to be suboptimal.

(i.e., CEOs who work for banks headquartered in states that differ from the CEOs' birth states).[6] We focus on mortgage lending to take advantage of the granular Home Mortgage Disclosure Act (HMDA) data through which we can observe the outcome, timing, and most importantly, location of each mortgage application. The unit of analysis is at the bank-county-year level in most specifications and all regression specifications include bank and county-year fixed effects.[7] This means that we compare the branching and lending decisions made by the same bank in two similar counties in the same year that differ only in their proximity to the CEO's birth county.

Overall, we find strong evidence of differential branching and lending policies near bank CEOs' hometown areas. Within the same bank, counties located one standard deviation closer in log distance to the CEO's hometown are associated with a 10.2% higher mortgage origination volume. We also find that banks have approximately 2.4% more branches in counties located one standard deviation closer in log distance from the CEO's hometown. Moreover, the effects are stronger for CEOs who also complete their undergraduate degree in their birth state. This is consistent with the idea that individuals who spend more time in their childhood home states display a stronger bias toward their hometown.

These estimations are robust even after we control for the proximity to the bank's headquarters (HQ) and a large set of loan-, bank-, and CEO-level characteristics (e.g., education, experience, and pay elements). We also use a methodology developed by Oster (2019) and find that, in order to explain away the entire effects of CEO hometown proximity, the selection of

[6] As shown in Appendix 7, we obtain robust results using the full sample of local and non-local CEOs.

[7] In addition, we also perform loan-level regressions on mortgage approvals (Panel B of Table 2) and mortgage default (Table 6). Loan-level regressions allow us to control more directly for applicant-level information, such as applicant gender, race, and income, which are important determinants of mortgage approvals and defaults.

unobserved omitted variables would need to be 2.2 to 16.8 times larger than the selection of observables. This is highly unlikely, given that we already include a large set of fixed effects and control variables in the regressions. Furthermore, we also obtain robust results using a subsample of banks with CEO turnover events that are caused by either the death or illness of a CEO or by a pre-announced CEO succession plan. This set-up introduces useful variation by creating the need for the board to replace a CEO for reasons unrelated to local branching or lending decisions. Consistent with our main findings, we observe that following CEO turnovers, banks open more branches and lend more in locations closer to the hometown of the incoming CEO.

Next, we show evidence of a CEO's influence on hometown lending. As loans are ultimately approved by the loan officer, one could be concerned that there is little room for CEOs to exert their influence. However, this does not appear to be the case. First, since we find that there is an increase in the number of bank branches near the incoming CEO's hometown following a CEO turnover, this already points to CEOs playing an active role in influencing local branching decisions and lending outcomes. Second, we examine changes in bank lending in response to severe natural disasters. As natural disasters increase the demand of credit in affected areas and put immediate pressure on banks to increase lending (Cortés and Strahan (2017)), banks need to decide whether to reallocate credit to disaster-affected areas. Given the ad-hoc nature of such events, all reallocation decisions need to be approved by the CEO. Consistent with CEOs playing an active role in shaping local lending outcomes, we observe an increase in lending in response to natural disasters that occur closer to the CEO's hometown compared to those that occur farther away.[8] Finally, we show that hometown lending is more prevalent when CEOs have a stronger

[8] In unreported analyses, we find that loans originated near CEOs' hometowns following natural disasters have lower default rates. This suggests that CEOs expand lending in their hometown following natural disasters to take advantage

influence within their bank. In sum, our results suggest that CEOs play a central role in hometown lending.

Importantly, while we show that CEOs have a direct influence on credit policies in their hometown areas, we do not discard the role of local branch managers or credit officers. Instead, we argue that the CEO plays a central role in the process and that the hometown lending effects could come from both the CEO and local employees who, as a result of hometown commonality and potential interactions with the CEO, might exert more effort in the lending process (Duchin and Sosyura (2013)).

Having established that banks implement a differential lending and branching policy near their CEOs' hometown areas, we next explore the underlying cause(s) of this effect. We find a collective body of evidence that supports the hometown advantage and conflicts with the agency explanation. First, we find that loans originated closer to a CEO's hometown have significantly lower rates of default. Specifically, loans originated one standard deviation closer in log distance to the CEO's hometown are 6.9% less likely to become delinquent relative to the mean default rate of 1.4%. Importantly, these estimates take into account applicants' average FICO scores and loan-to-value ratios; thus, they can be viewed as capturing incremental subjective attributes over and above the variation attributable to borrowers' "hard" risk characteristics. These results support the hometown advantage explanation, that, as a result of superior information, banks originate more loans and make more informed lending decisions in areas proximate to the CEO's hometown.

Second, we use a methodology similar in spirit to the procedure employed by Rajan, Seru and Vig (2015) to examine a bank's utilization of soft borrower information in making lending

of their superior local knowledge, which is especially important to aid lending in disaster-affected areas. The evidence, therefore, is consistent with the hometown advantage explanation.

decisions. Rajan et al. (2015) argue that when more information is employed to aid lending decisions, the variance in the terms of the contract should increase as banks are better able to discriminate between “good” and “bad” borrowers (cf. Skrastins and Vig (2019)). Consistent with the hometown advantage explanation, we find that loans originated closer to a CEO’s hometown have less standardized contractual terms. Taken together, our results strongly support the hometown advantage explanation. This advantage could arise from the CEO’s superior information and/or their superior ability to appoint and motivate local employees to exert more effort in utilizing borrower information to make informed lending decisions.

We find additional evidence that supports the hometown advantage explanation. In the cross-section, we find that the hometown lending effects are stronger among poorer, female, and non-white applicants. Given that these groups of applicants are more informationally opaque because they tend to have less detailed credit histories (Cohen-Cole (2011), Ergungor (2010)), our results again suggest that hometown advantages allow banks to lend more to these groups of borrowers.

We also find that hometown lending has no detectable effect on aggregate bank outcomes. In particular, the fraction of mortgage lending in a CEO’s hometown county does not explain the bank’s total lending, mortgage lending, mortgage loan performance, profitability, or stock returns. The results indicate that credit is simply being reallocated from counties located farther away to counties proximate to the CEO’s hometown; on net, hometown lending does not harm shareholder wealth. The evidence is therefore at odds with the agency explanation.

Finally, we conduct an out-of-sample test on small business lending and find that within the same bank, branches located in counties nearer to the CEO’s hometown enjoy higher growth in small business lending. Interestingly, this effect is only detected among the smaller loans (amounts below $250,000) and not the larger ones (amounts above $250,000). As banks typically require small business owners to put up assets as collateral in order to secure large loans, banks do not need to rely on superior information to gain an advantage when making those loans. Again, this finding is consistent with the hometown advantage explanation.

II. Literature and Contributions

Our paper connects three strands of literature: on the economic effects of home bias, the unconventional factors that influence credit allocation decisions, and the idiosyncratic style of CEOs. The home bias literature mainly focuses on investor behavior and features an important debate on whether the home bias tendency reflects an information advantage or a behavioral bias. For instance, Coval and Moskowitz (1999) and Ivkovic and Weisbenner (2005) argue that a home bias reflects the investor's information advantage, while Pool et al. (2012) find no such advantage in local investing. More recently, the literature has extended the home bias analysis to corporate managers, showing that CEOs' home bias affects firms' employment policies (Yonker (2017a)) and mergers and acquisitions outcomes (Jiang et al. (2019)).

We contribute to this body of literature by providing evidence of a home bias on credit intermediaries' production outputs (bank credit allocation) as opposed to their production inputs (e.g., employment decisions). Focusing on bank credit allocation is a question of first-order importance, given the role of bank credits in local economic developments (Celerier and Matray (2019), Nguyen (2019), and Rice and Strahan (2010)). Consistent with information access being one of the most important forces in shaping lending transactions (Liberti and Petersen (2019)), we show that hometown loans make more use of borrower soft information and have lower default rates. Our results complement those of Jiang et al. (2019), who show that context matters as to when the information and the agency explanations become the main mechanisms through which a home bias manifests. Furthermore, by focusing on non-local CEOs, we are able to control for the potential confounding effects associated with banks' headquarters locations and obtain a clean estimation of CEOs' hometown effects.

We also contribute to the literature on unconventional factors that influence credit allocation decisions. These studies find that credit officers may reject a loan application because they are in a bad mood (Cortés, Duchin, and Sosyura (2016)) or feel the urge to reject an application following a streak of consecutive approvals (Chen, Moskowitz, and Shue (2016)). Analyzing peer-to-peer lending, Duarte, Siegel and Young (2012) find that the physical appearance of borrowers predicts loan approvals and that this effect is mainly due to information. Our paper extends this literature by uncovering a new factor—CEO childhood origins—that systematically explains lending outcomes.

Finally, our study is related to the literature that studies the impact of CEO attributes on corporate outcomes. Various studies have found that a CEO's life (Bernile, Bhagwat, and Rau (2017), Cronqvist and Yu (2017), and Schoar and Zuo (2017)), career experience (Custódio and Metzger (2014), Dittmar and Duchin (2016)), political ideology (Hutton, Jiang, and Kumar (2014)), and lifestyle (Cain and McKeon, (2016), Sunder, Sunder, and Zhang (2017)) affect corporate decisions. A key advantage of our study is that, unlike education, career moves, and other characteristics of managers that have been previously studied, birthplace is not a choice that CEOs can make. Therefore, our findings can be seen as additional evidence of a manager-specific effect on *within*-firm business policies.

III. Sample, Variable Construction and Methodology

A. Sample Construction

To construct our sample, we combine several data sources: (1) Call Report (FR Y-9C forms); (2) BoardEx; (3) hand-collected data regarding CEOs' birth county and birth state; (4) Home Mortgage Disclosure Act (HMDA); and (5) Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD).

First, we obtain a list of all publicly listed U.S. banks with available financial data from the Call Report (FR Y-9C forms) provided by the Federal Reserve Bank of Chicago. Second, we collect the names of the CEOs of these banks from the BoardEx database. BoardEx provides detailed biographical and employment information on the board members and top executives of nearly all publicly listed U.S. firms. Since BoardEx's full coverage begins in 1999, our sample period is 1999–2014.

Third, we hand collect information on the birth counties of bank CEOs from several sources. We start with NNDB.com and Marquis Who's Who, both of which provide detailed biographical data on high-profile individuals, including CEOs. If we are unable to obtain the data this way, we then use Ancestry.com to search for each CEO's birth and marriage certificates, where birth county information is occasionally available.[9] As a last resort, we perform extensive Google searches using the keywords "[CEO full name] + native of" and/or "[CEO full name] + born." This process allows us to identify CEO birth county information manually from multiple sources, including CEO appointment announcements, SEC filings, school donations, charity events, biographies, interviews, and obituaries.

[9] The richness of the information contained in birth and marriage certificates depends on the staff that complete them.

We are able to identify the birth counties for 485 out of 906 U.S.-born CEOs (54%) who work for 369 of the 738 banks (50%) in our sample.[10] Of the 485 CEOs, 171 (35%) work for banks headquartered in states that differ from their birth states. The proportion of non-local CEOs is comparable to that which is reported in Yonker (2017b) and suggests that many banks prefer hiring local-born CEOs to facilitate their regional expansion. To isolate CEOs' hometown lending from their banks' regional focus, we focus our analysis on only *non-local CEOs*, i.e., CEOs working for banks headquartered in states that differ from their birth states. For robustness, we also use a full sample of both local and non-local CEOs and display the results in Appendix 7.

Appendix 2 displays the number of non-local CEOs according to their birth states. We find a strong positive correlation of 0.80 between the number of non-local CEOs according to birth state and the state's population in 1950,[11] implying that our sample of non-local CEOs is evenly drawn from each state's population. This significantly reduces sample self-selection concerns and points to the exogeneity of our variable.

Fourth, we match this bank-level dataset to the HMDA database collected by the Federal Financial Institutions Examination Council (FFIEC). The HMDA database is a loan-level dataset that covers all mortgage applications that have been reviewed by qualified financial institutions. Specifically, an institution is required to disclose any mortgage lending under HMDA if it has at

[10] While this is a significant improvement over the prior literature (e.g., Bernile et al. (2017) identify the birth counties of about 31% of CEOs in the S&P 1500 sample), there remains a sample self-selection concern that we lose some CEOs whose birth counties cannot be identified precisely. To ensure that our conclusions regarding CEOs' hometown effects are not driven by unobservable factors that make sample inclusion more likely, we address this by using a standard Heckman (1979) two-step procedure and display the results in Appendix 7.

[11] 1950 is the median birth year of the CEOs in our sample.

least one branch office in any metropolitan statistical area and meets the minimum size threshold. In 2006 (the median year in our sample), this reporting threshold was $36 million in book assets.[12] Because of this low reporting threshold, all banks in our sample are included in the dataset.

Each loan application in the HMDA dataset contains information on borrower demographics (e.g., income, gender, and race), loan characteristics (e.g., loan amount applied for and its purpose), property type, decision on the application (e.g., approved, denied, or withdrawn), the year in which the application decision was made, and the lender's identifier. Most importantly, we also observe the location of the property underlying each mortgage application. This allows us to capture the geographical dimension of a bank's lending strategy (e.g., its lending volume and lending growth in a specific location) to test our hypothesis. We follow the prior literature and drop applications that were closed due to incompleteness or withdrawn by the applicant before a decision was made, and we winsorize the loan amount and applicant's income at the 2.5% right tail to minimize the effects of outliers. In the final step, we match our dataset to a list of branches of U.S. banks from the FDIC's SOD database.

B. Methodology

To examine a bank's branching and mortgage origination decisions in counties near its CEO's birth county, we estimate: (1) bank-county-year regressions; and (2) loan-level regressions. The bank-county-year regressions enable us to focus on a bank's decisions regarding branch network and credit availability at the county level. In contrast, the loan-level regressions allow us to control more directly for loan-level variables (e.g., applicant gender, race, and income), which are

[12] HMDA's reporting criteria can be found at https://www.ffiec.gov/hmda/reporterhistory.htm

important determinants of loan approvals. The bank-county-year specification takes the following form:

$$(1) \qquad Y_{ikt} = \alpha_{ikt} + \beta_1 \ln(\text{DIST\_HOMETOWN})_{ikt} + \phi_{ikt} + \omega_{it}$$

$$+ \text{Bank Fixed Effects} + \text{County-Year Fixed Effects} + \varepsilon_{ikt},$$

and the loan-level specification is as follows:

$$(2) \qquad Y_{ijkt} = \alpha_{ijkt} + \beta_1 \ln(\text{DIST\_HOMETOWN})_{ikt} + \phi_{ijkt} + \omega_{it}$$

$$+ \text{Bank Fixed Effects} + \text{County-Year Fixed Effects} + \varepsilon_{ijkt},$$

where i indexes bank, j indexes loan, k indexes county, and t indexes year. Φ and ω are a vector of loan and bank controls, respectively. The dependent variable in the bank-county-year regressions is either a lending or branching outcome (ln(MORTGAGE_LOANS), MORTGAGE_GROWTH, APPROVAL_RATE, and ln(BRANCHES)) defined at the bank-county-year level. The dependent variable in the loan-level regressions is APPROVED, a dummy variable that equals one if a loan application is approved and zero otherwise. Our key explanatory variable ln(DIST_HOMETOWN)$_{ikt}$ is the natural logarithm of the physical distance[13] (in kilometres (km)) between a CEO's birth county and the county in which the branching and lending decisions take place.[14] The advantage of using this variable is that it captures the continuous nature of a CEO's hometown bias.

[13] Geographic coordinates (longitude and latitude) are obtained from the U.S. Census (2014) Gazetteer.

[14] While we cannot completely rule out the possibility of neighborhood rivalries (i.e., two adjacent regions developing a dislike for one another), this concern would be averaged out in a large sample. In Appendix 4, we obtain consistent

All regression specifications include ln(DIST_HQ), the natural logarithm of the physical distance between a bank's headquarters (HQ) and the counties where the mortgage and branching decisions take place. This allows us to further account for the potential effects of headquarters' proximity on local lending decisions (Stein (2002)). In addition, we also include a host of bank and loan controls. Bank controls in both the bank-county-year and loan-level specifications include: ASSETS, LEVERAGE, ROA, TOTAL_LOANS, and DEPOSITS. Loan controls in the bank-county-year specification are the bank-county-year averages of ln(APPLICANT_INCOME), LOAN_TO_INCOME, %FEMALE_APPLICANTS, and %NON_WHITE_APPLICANTS received on mortgage loan applications. Loan controls in the loan-level regressions are ln(APPLICANT_INCOME), LOAN_TO_INCOME, FEMALE, AFRICAN_AMERICAN, ASIAN, and OTHER_RACES.[15] Appendix 1 displays all variable definitions.

Both the bank-county-year-level and loan-level specifications include bank fixed effects (Bank FE) and county-year fixed effects (County-year FE). The inclusion of bank fixed effects absorbs all time-invariant bank-specific factors, allowing us to compare the mortgage and branching decisions of the same bank across different counties, conditional on the distance between the county and the CEO's hometown. Bank fixed effects also control for potential CEO-bank matching based on time-invariant bank characteristics (Custódio and Metzger (2014)).

The inclusion of county-year fixed effects removes all time-varying county-level factors, including demographic, social, economic, and demand-side factors related to local business cycles,

results using an alternative variable, HOMETOWN_STATE—a dummy variable that equals one if the CEO's birth state is the same as the state in which the lending and branching decisions take place and zero otherwise.

[15] OTHER_RACES is a dummy that equals one if the applicant is an American Indian, Alaska Native, Native Hawaiian, or Other Pacific Islander.

industry consumption, and housing demand (Gilje, Loutskina, and Strahan (2016)). In addition, county-year fixed effects also control for changes in state-level regulations, such as anti-predatory lending laws, that could affect mortgage origination behavior across different locations (Agarwal, Amromin, Ben-David, Chomsisengphet, and Evanoff (2014)).

With these fixed effects in place, our coefficient of interest, β_1, compares the branching and lending decisions of the same bank between two otherwise similar counties in the same year that differ only in their distance from the CEO's hometown. In other words, our regressions are identified by two sources of variation: (1) the varying distance between a CEO's hometown and different counties; and (2) changes in the distance between the CEO's hometown and a given county as a result of CEO turnover within the same bank.[16]

[Table 1 around here]

Table 1 displays the summary statistics. The average distance between a CEO's birth county and the county in which the mortgage originations and branching decisions take place is around 1,503 km. There is also substantial heterogeneity in this distance, with the standard deviation being 1,042 km. The average mortgage approval rate is 60.3%; that is, approximately 6 out of every 10 mortgage applications are approved in an average bank-county-year. The average borrower earns about $88,490 per year and applies for a mortgage loan of $121,700, implying a loan-to-income ratio of 1.4.

[16] For example, in 2003, Charles Prince (born in Lynwood, California) replaced Sandy Weill (born in Brooklyn, New York) as the CEO of Citigroup. This produces a change in the distance between the CEO's hometown and a given county.

IV. Main Analysis: Does Proximity to CEO's Hometown Affect Lending and Branching?

A. Main Results

In Panel A of Table 2, we present our baseline regression results that examine the effect of proximity to a CEO's hometown on the bank's lending and branching policies. Analyzing the data at the bank-county-year level allows us to focus on a bank's decisions regarding branch network and credit availability at the county-level, which are within the purview of the CEO.

[Table 2 around here]

The dependent variables in Panel A include: ln(MORTGAGE_LOANS), the natural logarithm of the nominal amount of mortgage loans originated by a bank in a county-year (Column (1)); MORTGAGE_GROWTH the percentage change in mortgage originations by a bank in a given county relative to the prior year (Column (2)); APPROVAL_RATE, the number of approved mortgage applications divided by the total number of applications received by a bank in a county-year[17] (Column (3)); and ln(BRANCHES), the natural logarithm of the number of branches a bank has in a county-year (Column (4)).

Across all outcome variables, the coefficient estimates on ln(DIST_HOMETOWN) are statistically significant and economically sizeable. For instance, the point estimate in Column (1) indicates that, within the same bank, branches located one standard deviation farther in log distance from the CEO's hometown are associated with a 10.2% (= –0.119 x 0.861) lower mortgage

[17] This variable normalizes the number of approved applications by loan demand that a bank receives in a county-year. It therefore accounts for significant demand-related variations arising from the fact that there is a very high demand for mortgages across the U.S. in the period 1999–2006, which is followed by a crash during the 2007–2010 financial crisis (Gilje et al., 2016). Holding other loan and applicant characteristics constant, APPROVAL_RATE measures a bank's willingness to supply mortgage credit in a county-year.

origination volume. In addition to mortgage lending outcomes, the model in Column (4) focuses on the number of bank branches, where the estimate indicates that banks have approximately 2.4% (= –0.028 x 0.861) fewer branches in counties located one standard deviation farther in log distance from the CEO's hometown. Given the role of bank branch networks in promoting local lending (Gilje et al., 2016), opening branches is an important channel through which CEOs influence lending activities in the vicinities of their hometowns.

In Panel B of Table 2, we augment the bank-county-year results with loan-level regressions that examine the effect of proximity to a CEO's hometown on the likelihood of mortgage approval. One advantage of the loan-level analysis is that it allows us to control more directly for other important determinants (e.g., applicant gender, race, and income) in the loan approval process. Its disadvantage, however, is that it requires significant computing resources. Further, the loan-level analysis does not also allow us to capture aggregate lending and branching outcomes of the bank at the county level. As such, we use the bank-county-year regressions as our main specification in the paper.

The dependent variable is a dummy variable that equals one if a mortgage application is approved and zero otherwise. Consistent with our hypothesis that banks lend more in proximity to their CEOs' hometowns, the coefficients on ln(DIST_HOMETOWN) are statistically significant well below the 1% level. The magnitude of the coefficient estimates on ln(DIST_HOMETOWN) is stable as we progressively include more fixed effects in the model. The results are also economically meaningful. If we compare lending by the same bank located in two otherwise similar counties that vary only in their proximity to the CEO's hometown, the loans originated in branches located one standard deviation farther in log distance to the CEO's hometown are 2% (= –0.023 x 0.861) less likely to be approved (Column (4)).

It is also comforting to note that the coefficients on the control variables have the expected signs. We find that lower income, female, and non-white applicants are less likely to have their mortgage applications approved. These groups of applicants tend to have a less detailed credit history and thus face a lower likelihood of approval (Ergungor (2010)). Overall, we find strong evidence of differential lending and branching policies with regards to proximity to bank CEOs' hometowns. In Sections V and VI, we show that this effect is mainly driven by CEOs' hometown advantage.

B. Robustness of the Baseline Results

1. Influence of Large States

One concern related to our results is that the positive relationship between the proximity to a CEO's hometown and credit activities could be driven by the fact that many CEOs grow up in a few large states, such as New York or Pennsylvania, and these states also have more economic and credit activities. While the inclusion of county-year fixed effects already controls for all time-varying location characteristics and addresses this problem to a large degree, we perform two additional tests to further alleviate this concern. First, we exclude all loans originated by banks led by CEOs who grew up in the top three states of origin for CEOs: New York, Pennsylvania, and Ohio.[18] Approximately 26% of CEOs in our sample are from those states. As shown in Appendix 3, the re-estimated coefficients on ln(DIST_HOMETOWN) are highly significant and similar in magnitude to those observed in Panel A of Table 2 for our baseline regressions.

[18] Our results are not sensitive to the number of states excluded from the regressions. In unreported analyses, we obtain robust results when we exclude, for instance, the top five CEO home states. Our results are also robust when we define 'large states' based on the state population or the number of bank headquarters in the state.

Second, we follow Jiang et al.'s (2019) procedure and run placebo tests using randomized CEO birth counties.[19] The randomization process reshuffles CEO's birth counties but maintains the original data structure by drawing CEO's birth counties from the original distributions without replacement. We then use the randomized data to re-estimate the regressions in Columns (1)–(4) from Panel A of Table 2. We perform 1,000 simulations and plot the distribution of the coefficient estimates on ln(DIST_HOMETOWN) in Figure 1. Panels A, B, C, and D display the distributions for ln(MORTGAGE_LOANS), MORTGAGE_GROWTH, APPROVAL_RATE, and ln(BRANCHES) respectively.

[Figure 1 around here]

Across all outcome variables, the average coefficient estimates using the placebo data are 0.000. In contrast, the coefficient estimates using the actual data are significantly larger in absolute terms. For instance, the estimate using the actual data for the regressions on ln(MORTGAGE_LOANS) is –0.119, which is over 18 standard deviations from the mean estimate from the placebo data. The mean estimate of 0.000 using placebo data suggests that our results do not capture omitted variables that are simultaneously correlated with the clustering of CEOs' hometowns and higher levels of credit activities (otherwise, we would still observe large and statistically significant placebo estimates). Overall, the findings indicate that our main results are not driven by large states or, more generally, omitted variables at the location-level.

2. Other Robustness Tests

This section presents other robustness tests on the baseline results. In Panel A of Appendix 4, we use an alternative explanatory variable HOMETOWN_STATE, which is a dummy that equals one

[19] We also run placebo tests using randomized CEO birth states and arrive at a similar conclusion.

if the CEO's birth state and the state in which the mortgage originations and branch decisions take place are the same. Consistent with our baseline findings, Panel A indicates that the CEO's birth state exhibits higher levels of mortgage origination volume, mortgage growth, and approval rates and has more bank branches when compared to other states. Panel B of Appendix 4 indicates that the magnitude of the CEO's hometown effects is strongest within a small radius from the CEO's birth county (the large coefficients on HOMETOWN<200KM, 200KM<HOMETOWN<400KM and 400KM<HOMETOWN<600KM) implying that the hometown lending effects are local. Moreover, the diminishing effects of hometown lending suggest that our results are not driven by specific locations (e.g., New York City or Chicago) or, more generally, location-specific omitted variables.

Appendix 5 shows that our results are robust to the inclusion of additional control variables at the CEO level (including CEO compensation, age, and whether the CEO is an Ivy League graduate, has an MBA degree, was born during depression years, began their career during a recession, is overconfident, and has military experience) and at the bank level (the proportion of outside directors and the G-Index developed by Gompers, Ishii, and Metrick (2003)).

In Appendix 6, we use a methodology developed by Oster (2019) to assess the potential bias from unobservable omitted variables. This test computes the share of the variation that unobservable variables need to explain (relative to the variation explained by the control variables included in the estimations) in order to reduce the effect of interest to zero. This share is denoted as δ, which is defined as $\frac{\beta_{Full}}{\beta_{Restrict}-\beta_{Full}} \text{x} \frac{R_{Full}-R_{Restrict}}{R_{Max}-R_{Full}}$, where $\beta_{Restrict}$ is the coefficient on ln(DIST_HOMETOWN) from the model using a restricted set of controls, and β_{Full} is the coefficient on ln(DIST_HOMETOWN) from the model using a full set of controls. The implementation of Oster's (2019) test requires specifying the value of R_{Max}, which is the R^2 from a hypothetical regression that includes both observed and unobserved controls. Based on experimental evidence, Oster (2019) recommends setting $R_{Max} = 1.3R_{Full}$, where R_{Full} is the R^2 from a regression that includes the full set of control variables.

As shown in Appendix 6, the values of δ range from 2.2 to 16.8, which are significantly higher than the robustness benchmark of 1 recommended by Oster (2019). The interpretation is that the unobservables need to be at least 2.2 to 16.8 times as important as the observables to completely reduce the coefficient of interest to zero. This is highly unlikely given that our regression specifications already include a large set of fixed effects and important determinants of lending outcomes. An alternative approach to assess the robustness of the results is to estimate a set of possible ranges for β, which is $[\beta^*, \beta_{Full}]$, where the bias-adjusted treatment effect is $\beta^* = \beta_{Full} - (\beta_{Restrict} - \beta_{Full})\ x\ \frac{R_{Max}-R_{Full}}{R_{Full}-R_{Restrict}}$. If the range does not include zero, the estimates are considered robust. Appendix 6 indicates that all the estimated ranges for β do not include zero, giving us further confidence that unobservable omitted variables do not drive our results.

Panel A of Appendix 7 displays other robustness tests on our baseline findings in Panel A of Table 2. We find that none of the following empirical variations have a material impact on our baseline results: (1) performing our regressions on a standard Heckman (1979) two-step procedure to account for potential self-selection biases arising from the fact that we lose CEOs whose birth counties cannot be identified;[20] (2) excluding the smallest 10% of banks (in terms of total assets)

[20] The first step of the Heckman procedure estimates the probability that a CEO is included in our sample. The sample in the first step includes: (1) banks led by non-local CEOs that are included in the main sample and; (2) banks that we are unable to include in the sample due to missing information regarding CEO's birth counties. The dependent variable in the first step is a dummy that equals one if a CEO is included in the sample and zero otherwise. All regression specifications include bank and county-year fixed effects and a full set of control variables (ln(DIST_HQ), ASSETS,

since one could argue that small banks have limited geographical coverage and, as a result, there is no meaningful variation between the CEO's hometown and lending locations; (3) excluding the largest 10% of banks since the CEOs of very large banks are less likely to influence local lending; (4) excluding data covering the 2007–2009 financial crisis; (5) controlling for the staggered deregulation of interstate bank branching laws since our results could be confounded with increases in lending following the relaxation of bank branch restrictions (Rice and Strahan (2010)); and (6) using the full sample that includes both non-local and local CEOs.

Panel B of Appendix 7 addresses the concern that our baseline results could be driven by changes in a bank's funding structure (i.e., depositors shift their money to banks led by CEOs from their hometowns) resulting in a deposit surplus and a higher lending growth. As shown in Panel B, proximity to a CEO's hometown is *not* related to the local deposit growth rate.

C. CEOs' Degree of Hometown Bias

Our main measure of a CEO's hometown proximity is based on their birth county. This proxy, however, may not capture the full extent of a CEO's hometown bias if, for instance, the CEO's family relocates soon after their birth or if the CEO works away from their hometown. We refine this proxy and show in Table 3 that our baseline results become stronger for CEOs who undertake an undergraduate degree in the same state (HOMETOWN_UG x ln(DIST_HOMETOWN)) in which they were born.

LEVERAGE, ROA, DEPOSITS, TOTAL_LOANS, ln(APPLICANT_INCOME), LOAN_TO_INCOME, %FEMALE_APPLICANTS, and %NON_WHITE_APPLICANTS). The second stage of the Heckman procedure includes LAMBDA, which contains information from the first step to control for the unobservable factors that make sample inclusion more likely.

[Table 3 around here]

These results are consistent with both the hometown advantage and the agency explanations. Individuals who study for their first degree in their birth state are likely to spend more time there and could have better access to information on their hometown areas as a result. Similarly, these individuals could also be more deeply rooted in the local community and thus have a greater incentive to favor their hometown for their own private benefit. Notwithstanding the reasons, the results help strengthen our interpretation of the hometown lending effects.

D. Evidence from CEO Transitions

As our regressions include bank fixed effects, the effects documented in Table 2 are identified via within-bank CEO changes. One concern with taking this approach is that CEO turnover may be driven by changes in bank characteristics that also affect the branching and mortgage decisions made near the CEO's hometown. For instance, banks with a plan to expand to California could be more likely to appoint a California-born CEO and simultaneously implement strategies to open more branches and increase lending in California.

In this section, we focus on two subsamples in which CEO transitions are less likely to be driven by the bank's desire to change its lending and branching strategies. First, we focus on a subsample of banks that experience changes in their CEOs for plausibly exogenous reasons (Panel A of Table 4). For instance, if the current CEO unexpectedly passes away, this would force the board to appoint a new CEO. Given that a successor CEO would need to be appointed at a relatively short notice, it is less likely that the new CEO would be selected for reasons specifically related to local lending decisions. While the selection of an incoming CEO is not entirely random, this set-up still introduces some useful external variation by creating the need to appoint a CEO for reasons that are not plausibly related to local lending decisions.

Following Nguyen, Hagendorff, and Eshraghi (2018), we consider a turnover to be exogenous if it meets at least one of the following criteria: (1) the outgoing CEO departs as a result of death or illness; (2) the outgoing CEO is of the natural retirement age (i.e., 60 or older) at the time of the turnover; or (3) the turnover occurs as part of the bank's succession plan (with the date of departure announced at least six months prior to the departure). In total, 59% of the CEO turnovers in our sample are classified as exogenous.

Second, we focus on a subsample of internal CEO turnovers, in which the incoming CEO was already employed by the bank (Panel B). Internal successions often reflect a desire for continuity in a bank's strategy (Dittmar and Duchin (2016)). Therefore, the choice of the CEO is less likely to reflect a desire to change a bank's lending policies.

We estimate regressions that compare bank branching and mortgage lending decisions one year after the turnover of the CEO and one year before the turnover. The dependent variables are *changes* in post-turnover branching and lending outcomes (e.g., mortgage origination volume one year after the turnover minus mortgage origination volume one year before the turnover). The key independent variable of interest is the change in the proximity to the CEO's hometown resulting from the turnover (Δln(DIST_HOMETOWN)). The change in the proximity to the CEO's hometown is positive (negative) when the hometown of the incoming CEO is farther from (nearer to) a given location when compared to the location of the outgoing CEO's hometown. Similar to the proximity variable, all control variables are the differences from one year after the turnover and one year before the turnover.[21]

[Table 4 around here]

Across both panels in Table 4, the coefficient estimates on Δln(DIST_HOMETOWN) are negative and statistically significant across all columns. This indicates that banks increase mortgage lending (Columns (1)–(3)) and open more branches (Column (4)) in locations closer to the hometown of the incoming CEO. Overall, the findings suggest that resources are being reallocated within banks to facilitate lending in the hometown of the incumbent CEO. We further explore this argument in Section VI.A.

E. CEOs' Influence on Hometown Lending

As loans are screened and ultimately approved by loan officers, one might wonder how much influence CEOs have over local branching and lending outcomes. In this section, we discuss and conduct several analyses to show that CEOs play a pivotal role in shaping credit policies at the local level.

First, the analysis of CEO transitions in the previous section is direct evidence of a CEO's pivotal influence in the credit allocation process. If CEOs do not matter, we should not observe an increase in lending in the hometown of the incoming CEO following a CEO turnover. Upon taking over the reins, CEOs could implement policies to open more branches near their hometowns, which would lead to an increase in local lending (Gilje et al. (2016), Nguyen (2019)). This is precisely what we find in Table 4, which directly points to the active role of the CEO in influencing local

[21] As banks do not change the location of their headquarters as a result of CEO turnovers, Δln(DIST_HQ) is always zero. Therefore, this variable is dropped from the regressions.

lending. Second, CEOs could exert their influence locally by appointing their friends or contacts as local branch managers. Third, as CEOs regularly review branch performance and intervene in the operations of individual branches,[22] their preferences with respect to hometown lending can be conveyed to local branch managers and shape their influence on credit availability at the local level.

To augment the above discussions, we conduct two additional tests to demonstrate CEOs' direct influence on local lending decisions. As a first test, we examine changes in bank lending in response to severe natural disasters. The idea is that since natural disasters increase credit demand in affected areas and put immediate pressure on banks to increase lending, CEOs need to make the difficult decision of whether to reallocate credit to the areas affected by the disaster. As this requires banks to cut lending from their unaffected markets in order to have enough liquidity to support disaster-affected areas (Cortés and Strahan (2017)), CEOs are likely to have significant input in the decision or make the decision themselves. This allows us to attribute local lending outcomes to the CEO.

We match data from the Spatial Hazard Events and Losses Database for the US (SHELDUS) constructed by the University of South Carolina to our sample. SHELDUS is a county-level dataset that contains the date, type (e.g., wildfire, earthquake, hurricane, etc.), the severity of disasters (e.g., fatalities, property losses, etc.) and locations of the affected counties. To examine how

[22] For instance, if the CEO believes that a specific branch is growing too fast (which could attract attention from regulators), they may intervene by raising the concern directly with the branch manager. While such communications are infrequent, a CEO's preferences (e.g., whether the branch is encouraged to continue pursuing aggressive lending) can be learned by local branch managers and thereby shape local lending behavior. This is consistent with survey evidence from Graham, Grennan, Harvey, and Rajgopal (2019), which shows that CEO values are communicated top–down and influence the behavior of local employees. We thank an anonymous bank CEO for providing this insight into local branching and lending procedures.

proximity to the CEO's hometown affects the bank's response to natural disasters, we regress our outcome variables on the interaction between ln(DIST_HOMETOWN) and DISASTER_SEVERITY (defined as the proportion of the number of fatalities to the county's population).

[Table 5 around here]

As shown in Panel A of Table 5, the coefficient estimates on DISASTER_SEVERITY x ln(DIST_HOMETOWN) are statistically negative. Thus, banks are more likely to increase lending in response to natural disasters that occur closer to the CEO's hometown than in response to those that occur farther away. As CEOs are likely to be responsible for making this decision, the results point to the CEO's potential influence on local lending decisions. In unreported analyses, we find that loans originated near CEOs' hometowns following natural disasters have lower default rates. Thus, consistent with the hometown advantage explanation, CEOs expand lending in their hometown following natural disasters to take advantage of their local knowledge, which is especially important in facilitating lending in disaster-affected areas.

As a second test, we examine whether our baseline results differ when CEOs are more powerful. If CEOs have an influence on local lending, we should observe stronger hometown effects in banks with more powerful CEOs since they have more freedom to implement their preferred policies. In contrast, if CEOs are not involved in shaping local lending decisions, our baseline results should not depend on their power. To test for this, we regress our outcome variables on the interaction between ln(DIST_HOMETOWN) and POWERFUL_CEO (which is the sum of two indicator variables on whether the proportion of inside directors on the board is above the sample median and whether the CEO's tenure is above the sample median).[23]

Panel B of Table 5 indicates that the CEO hometown effects become even more pronounced when the CEO has more power relative to the bank's board of directors (negative coefficient on POWERFUL_CEO x ln(DIST_HOMETOWN)). The results suggest that CEOs do indeed have some influence on local lending and branching decisions. This influence becomes stronger when CEOs have more power vis-à-vis the boards as this presents a greater opportunity for CEOs' personal attitudes to shape branching and lending outcomes.

Importantly, while we show that CEOs have a direct influence on credit policies in their hometown areas, we do not discount the role of local branch managers or credit officers. Ultimately, loan officers are the ones responsible for loan screening and approval. Instead, we argue that the CEO has a central role to play in the process and that loan officers are not acting in isolation.

V. Is Hometown Lending Superior?

A. Loan Performance

So far, we find that counties located closer to a CEO's hometown enjoy greater lending and better access to bank branches than those located farther away. In this section, we attempt to disentangle the underlying causes of the CEO's hometown lending effects by tracking the ex-post performance of mortgage loans. If the hometown lending effects are driven by agency conflicts, then hometown loans would be suboptimal; thus, they should underperform in the long run. In contrast, if CEOs

[23] An insider-dominated board of directors is less likely to intensely monitor the CEO (Weisbach (1988)). Similarly, CEOs with a longer tenure tend to have a greater influence over the board (Coles, Daniel, and Naveen (2014)).

implement policies to lend more near their hometowns to exploit their hometown advantages, then the performance effect of hometown loans should be positive.

To distinguish between these hypotheses, we exploit a dataset compiled by Fannie Mae (Fannie Mae Single-Family Loan Performance Data) that tracks the ex-post performance of individual loans.[24] This dataset covers approximately one-quarter of the U.S. mortgage market and provides loan-level monthly status updates, including information on loan delinquencies. Following Cortés et al. (2016), we consider a loan to be delinquent (LOAN_DELINQUENCIES) if it becomes 90 days delinquent or enters foreclosure during the first two years of the loan's life.[25] The analyses are performed at the loan-level. This allows us to control for loan-level control variables such as applicant gender, race, and income, which are important determinants of ex-post loan performance. All regressions include county-year and bank fixed effects and control variables similar to those in Panel B of Table 2. We also include two additional controls for borrower risk made available in the Fannie Mae dataset (i.e., the applicant's FICO score (FICO) and the loan amount borrowed as a ratio of the value of the property (LOAN_TO_VALUE)).

[Table 6 around here]

The results presented in Table 6 indicate that loans originated closer to a CEO's hometown have lower rates of defaults. The coefficient estimates are statistically significant and indicate that loans originated one standard deviation closer to the bank CEO's hometown are 0.097% (=

---

[24] The Fannie Mae Single-Family Loan Performance Data is publicly available and can be accessed at: https://www.fanniemae.com/portal/funding-the-market/data/loan-performance-data.html.

[25] The advantage of focusing on the early years of a loan's life is that the borrower's characteristics would still resemble those at the time of the application review (Rajan et al. (2015)). Our results are robust to using alternative default windows, such as three or five years.

0.00113 x 0.861) less likely to default (Column (3)). Relative to the average default rate of 1.4%, this estimate corresponds to an economically significant marginal effect of 6.9%. Importantly, these estimates already account for the "hard" quantitative components of loan risk (i.e., FICO score and the loan-to-value ratio); thus, they can be viewed as capturing incremental subjective attributes over and above the variation attributable to common borrower risk characteristics. Therefore, these results support the hometown advantage explanation that banks have superior information on their CEOs' hometown areas, which allows them to originate more loans and make more informed lending decisions (Agarwal and Hauswald (2010)). The results are at odds with the agency explanation that CEOs implement policies to lend more in their hometowns in the pursuit of private benefits.

B. The Use of Soft Information

To sharpen our hometown advantage interpretation, we next examine whether loans originated near CEOs' hometowns incorporate more soft information. To test for this, we employ a methodology similar in spirit to the procedure used in Rajan et al. (2015). The intuition for this test can be illustrated using the following example. Consider two borrowers with identical hard information, but different soft information content. In the absence of soft information, both borrowers should receive similar loans contracts. In contrast, if banks have superior soft information in areas near their CEOs' hometowns, they should be able to distinguish "good" borrowers from "bad" borrowers and, as a result, grant more favorable loan terms to "good" borrowers (cf. Skrastins and Vig (2019)). In other words, when more soft information is employed to aid lending decisions, we should observe more dispersion in contractual terms.

We follow Skrastins and Vig (2019) and use three measures to capture dispersion in contractual terms. The first two measures focus on dispersion in the loan amount: the standard deviation (Column (1)) and interquartile range (Column (2)) of the loan amount of loans originated in a given bank-county-year. The third measure is the residual loan amount (Column (3))—the variation in the loan amount that cannot be explained by observable borrower information and other contractual characteristics.[26] As the example above illustrates, the greater the amount of soft information used to aid lending decisions, the larger these measures. The unit of analysis is at the bank-county-year level, and all regressions include county-year and bank fixed effects and control variables, as per equation (1).

[Table 7 around here]

Table 7 reports the results. Across all outcome variables, we find consistent evidence that loans originated near a CEO's hometown have more dispersed contractual terms. Specifically, the standard deviation and interquartile range of loan amounts are 3.4% (= –0.039 x 0.861) and 2.2% (= –0.026 x 0.861) higher for loans originated one standard deviation closer to the bank CEO's hometown. Similarly, proximity to a CEO's hometown is also associated with a higher residual loan amount. These findings suggest that more soft information is being used in loans originated near a CEO's hometown.

[26] The residual loan amount is the residual from a regression of observable loan and borrower characteristics on ln(LOAN_AMOUNT). The dependent variable is ln(LOAN_AMOUNT), the natural logarithm of the loan amount of loans originated in a given bank-county-year. The explanatory variables are: %FEMALE_APPLICANTS, %NON_WHITE_APPLICANTS, %OCCUPIED HOMES, %REFINANCING, ln(APPLICANT_INCOME) and %CONVENTIONAL_LOANS. For brevity, the results of this regression are unreported. They are available upon request.

In summary, our findings that hometown loans have lower default rates and utilize more soft information strongly support the hometown advantage explanation. This advantage could arise from the CEO's superior information and/or their superior ability to appoint and motivate local employees. As for the latter, it is possible that hometown commonality facilitates the interactions between CEOs and local employees, which in turn incentivizes employees to exert more effort in the collection and utilization of borrower soft information. Regardless of the mechanisms, our findings show that more information is being used in hometown loans, which leads to an elevated loan performance.

VI. Additional Results

A. Bank-Level Evidence

Having shown that loans originated nearer to the CEO's hometown have different ex-post outcomes and that the effect is mainly driven by the CEO's hometown advantage, a natural question that arises is whether CEO hometown lending also affects aggregate bank outcomes. While CEOs' hometown advantage allows banks to make more informed lending decisions near the CEOs' hometown areas, this effect could be offset by the lower loan quality in distant counties, leaving no effect on aggregate bank outcomes. To test for this, we regress %MORGAGE_LOAN_HOME_COUNTY (the fraction of a bank's mortgage lending originated in the bank CEO's birth county) on five bank-level outcome variables: (1) TOTAL_LOANS; (2) MORTGAGE_LOANS; (3) BAD_LOANS; (4) ROA; and (5) STOCK_RETS.

[Table 8 around here]

The estimates for all outcome variables in Table 8 are statistically insignificant. Thus, the proportion of mortgage lending in the CEO's hometown county cannot explain a bank's total lending (total loans divided by total assets), mortgage lending (mortgage loans divided by total assets), mortgage loan performance (bad loans divided by mortgage loans), profitability (return on assets), or shareholder wealth (annual stock returns). The non-results on TOTAL_LOANS (the proportion of total lending to bank assets) imply that CEOs do not expand total lending to accommodate greater hometown lending. Instead, lending is reallocated from areas that are farther away to areas that are closer to the CEO's hometown. Overall, these findings are again at odds with the agency hypothesis and support the interpretation that CEOs reallocate resources closer to their hometown to exploit their hometown advantage.

B. Cross-sectional Evidence

In Table 9, we examine how the hometown lending effects vary in the cross-section of borrowers to further understand the cause(s) underlying the CEO's hometown lending effects. If the effects are driven by the CEO's hometown advantage, they should be stronger among more informationally opaque, difficult-to-verify borrowers and become weaker when the decisions are more clear-cut. To test for this, we interact ln(DIST_HOMETOWN) with: (1) LOW_INCOME_APPLICANTS, a dummy that equals one if the average income of applicants received by a bank in a county-year is below the sample median and zero otherwise; (2) %NON_WHITE_APPLICANTS, the proportion of non-white applicants the bank receives in a county-year; and (3) %FEMALE_APPLICANTS, the proportion of female applicants the bank receives in a county-year.

[Table 9 around here]

The results in Table 9 indicate that the CEO's hometown lending effects are more pronounced among poorer (Panel A), non-white (Panel B), and female (Panel C) mortgage applicants—these are borrowers whose applications are traditionally more difficult to verify because they have less detailed credit histories and require more screening effort from the bank (Cohen-Cole (2011), Ergungor (2010)).[27] Therefore, superior information arising from a hometown advantage would allow banks to better evaluate opaque applicants, resulting in a greater lending volume targeted toward these applicants near the region of the CEO's hometown. These results strongly support the hometown advantage explanation.

C. Out-of-Sample Test: CEO Hometown Effects on Small Business Lending

Our main analyses focus on mortgage lending to take advantage of the granular HMDA dataset, in which we can observe the entire pool of loan-level applications, including the rejected applications, to separate loan demand from supply. In this section, we conduct an out-of-sample test and examine whether counties located nearer to the CEO's hometown also enjoy higher small business lending growth when compared to counties located farther away.

We obtain small business lending data from the Community Reinvestment Act (CRA) database compiled by the FFIEC. The data are aggregated at the bank-county-year level. The FFIEC categorizes small business loans into three size brackets according to the amount: (1) less than $100,000; (2) between $100,000 and $250,000; and (3) between $250,000 and $1,000,000. For each size bracket, we calculate the dependent variable, ln(SMALL_BUSINESS_LOANS),

[27] Cohen-Cole (2011), for instance, shows that non-white applicants tend to have a less detailed credit history than white applicants.

which is the natural logarithm of the nominal amount of small business loans originated by a bank in a county-year. All regressions include bank and county-year fixed effects.

[Table 10 around here]

The results in Table 10 confirm that within the same bank, counties nearer to the CEO's hometown exhibit a higher growth in small business lending. Importantly, this effect is only detected among the smaller loans (less than $250,000 (Columns (1)-(2)) and becomes insignificant for larger loans between $250,000 and $1,000,000 (Column (3)). As banks typically require small business owners to put up their assets as collateral to secure a large loan, they do not need to rely on superior information to gain an advantage on these loans. Furthermore, if CEOs lend more in their hometowns to seek recognition, the effect should concentrate among the largest loans as these would increase the CEO's visibility in their local communities.[28] Therefore, the findings are strongly consistent with the hometown advantage and again are at odds with the agency explanation.

VII. Conclusions

Our paper documents new evidence of a home bias on bank lending and branching outcomes. Focusing on bank lending outcomes is a question of first-order importance, given the impact of bank credits on local economic developments. We find that banks open more branches and make more lending near the bank CEO's childhood homes. The effects are stronger for CEOs who also

[28] In unreported tests, we repeat the bank-level performance analyses in Table 8 for small business lending. We find that the fraction of small business lending in the CEO's birth county does not explain the bank's total lending, loan performance, return on assets, or stock returns. The results support the hometown advantage explanation. These results are available upon request.

complete their undergraduate degree in their birth state, consistent with the idea that individuals who spend more time in their childhood home states display a stronger bias toward their hometown.

Consistent with information access being one of the most important forces in shaping lending transactions, we find that hometown lending is mainly driven by the superior information. Specifically, loans originated near the CEO's hometown have lower ex-post default rates and make more use of borrower soft information. Moreover, hometown lending is more salient among informationally opaque borrowers for which information access is needed to overcome financing frictions. Finally, we find that hometown lending does not affect aggregate bank outcomes, suggesting that credit is being reallocated from regions located farther away to regions proximate to the CEO's hometown. Taken together, our paper provides evidence that bank CEOs have advantages in their hometowns and that this matters for branching and credit allocation policies.

References

Agarwal, S.; G. Amromin; I. Ben-David; S. Chomsisengphet; and D. D. Evanoff. “Predatory lending and the subprime crisis.” *Journal of Financial Economics*, 113 (2014), 29-52.

Agarwal, S. and R. Hauswald. “Distance and Private Information in Lending.” *Review of Financial Studies*, 23 (2010), 2757-2788.

Bae, K-H; R. M. Stulz; and H. Tan. “Do local analysts know more? A cross-country study of the performance of local analysts and foreign analysts.” *Journal of Financial Economics*, 88 (2008), 581-606.

Bernile, G.; V. Bhagwat; and R. Rau. “What Doesn't Kill You Will Only Make You More Risk-Loving: Early-life Disasters and CEO Behavior.” *Journal of Finance*, 72 (2017), 167-206.

Cain, M. D. and S. B. McKeon. “CEO Personal Risk-Taking and Corporate Policies.” *Journal of Financial and Quantitative Analysis*, 51 (2016), 139-164.

Celerier, C. and A. Matray. “Bank-Branch Supply, Financial Inclusion and Wealth Accumulation.” *Review of Financial Studies*, 32 (2019), 4767–4809.

Chen, D. L.; T. J. Moskowitz; and K. Shue. “Decision Making Under the Gambler’s Fallacy: Evidence from Asylum Judges, Loan Officers, and Baseball Umpires.” *Quarterly Journal of Economics*, 131 (2016), 1181-1242.

Cohen-Cole, E. “Credit card redlining.” *Review of Economic and Statistics*, 93 (2011), 700-713.

Coles, J.; N. D. Daniel ; and L. Naveen. “Co-opted boards.” *Review of Financial Studies*, 27 (2014), 1751–1796.

Cornaggia, J.; K. J. Cornaggia; and R. Israelsen. “Where the heart is: Information production and the home bias.” *Management Science*, Forthcoming (2020).

Cortés, K.; R. Duchin ; and D. Sosyura. “Clouded judgment: The role of sentiment in credit origination.” *Journal of Financial Economics*, 121 (2016), 392-413.

Cortés, K.; P. E. Strahan. “Tracing out capital flows: How financially integrated banks respond to natural disasters.” *Journal of Financial Economics*, 125 (2017), 182-199.

Coval, J. D. and T. J. Moskowitz. “Home bias at home: Local equity preference in domestic portfolios.” *Journal of Finance*, 54 (1999), 2045-2073.

Cronqvist, H. and F. Yu. “Shaped by their daughters: Executives, female socialization, and corporate social responsibility.” *Journal of Financial Economics*, 126 (2017), 543-562.

Cross, R. L. and A. Parker. “How Managers Manage Social Networks.” In *The hidden power of social networks: Understanding how work really gets done in organizations*. Harvard Business Press (2004).

Custódio, C. and D. Metzger. “Financial expert CEOs: CEO’s work experience and firm’s financial policies.” *Journal of Financial Economics*, 114 (2014), 125-154.

Dittmar, A. and R, Duchin. “Looking in the Rearview Mirror: The Effect of Managers' Professional Experience on Corporate Financial Policy”. *Review of Financial Studies*, 29 (2016), 565-602.

Duchin, R. and D. Sosyura. “Divisional managers and internal capital markets.” *Journal of Finance*, 68 (2013), 387-429.

Duarte, J.; S. Siegel; and L. Young. “Trust and Credit: The Role of Appearance in Peer-to-Peer Lending.” *Review of Financial Studies*, 25 (2012), 2455-2484.

Ergungor, O.E. “Bank Branch Presence and Access to Credit in Low- to Moderate- Income Neighborhoods.” *Journal of Money, Credit, and Banking*, 42 (2010), 1321-1349.

Graham, J.; C. Harvey; J. Grennan; and S. Rajgopal. “Corporate Culture: Evidence from the Field.” Working paper, NBER (2019)

Gilje, E. P.; E. Loutskina; and P. E. Strahan. “Exporting liquidity: Branch banking and financial integration.” *Journal of Finance*, 71 (2016), 1159-1184.

Gompers, P.A.; J. L. Ishii; and A. Metrick. “Corporate governance and equity prices.” *Quarterly Journal of Economics*, 118 (2003), 107-155.

Heckman, J. J. “Sample selection as a specification Error”. *Econometrica*, 47 (1979), 153-161.

Hutton, I.; D. Jiang; and A. Kumar. “Corporate Policies of Republican Managers.” *Journal of Financial and Quantitative Analysis*, 49 (2014), 1279-1310.

Ivković, Z. and S. Weisbenner. “Local does as local is: Information content of the geography of individual investors' common stock investments.” *Journal of Finance*, 60 (2005), 267-306.

Jensen, M. C. and W. H. Meckling. “Theory of the firm: managerial behavior, agency costs and ownership structure.” *Journal of Financial Economics*, 3 (1976), 305–360.

Jiang, F.; Y. Qian; and S. E. Yonker. "Hometown biased acquisitions." *Journal of Financial and Quantitative Analysis*, 54 (2019), 2017-2051.

Kruger, P. "Corporate goodness and shareholder wealth." *Journal of Financial Economics*, 115 (2015), 304-329.

Liberti, J. M. and M. A. Petersen. "Information: Hard and Soft." *Review of Corporate Finance Studies*, 8 (2019), 1-41.

Malloy, C. J. "The geography of equity analysis." *Journal of Finance*, 60 (2005), 719-755.

Manzo, L. C., and D. D. Perkins. "Finding Common Ground: The Importance of Place Attachment to Community Participation and Planning." *Journal of Planning Literature*, 20 (2006), 335-350.

Masulis, R. and S. W. Reza. "Agency problems of corporate philanthropy." *Review of Financial Studies*, 28 (2015), 592-636.

Nguyen, D.D.; J. Hagendorff; and A. Eshraghi. "Does a CEO's cultural heritage affect performance under competitive pressure?" *Review of Financial Studies*, 31 (2018), 97-141.

Nguyen, H. L. Q. "Are credit markets still local? evidence from bank branch closings." *American Economic Journal: Applied Economics*, 11 (2019), 1-32.

Oster, E. "Unobservable Selection and Coefficient Stability: Theory and Evidence." *Journal of Business and Economic Statistics*, 37 (2019), 187-204.

Petersen, M. A. and R. G. Rajan. "Does distance still matter? The information revolution in small business lending." *Journal of Finance*, 57 (2002), 2533-2570.

Pool, V. K.; N. Stoffman; and S. E. Yonker. "No place like home: Familiarity in mutual fund manager portfolio choice." *Review of Financial Studies*, 25 (2012), 2563-2599.

Proshansky, H. M. "The city and self-identity." *Environment and Behavior*, 10 (1978), 147-169.

Rajan, U.; A. Seru, A; and V. Vig. "The failure of models that predict failure: Distance, incentives, and defaults." *Journal of Financial Economics*, 115 (2015), 237-260.

Rice, T. and P. E. Strahan. "Does credit competition affect small-firm finance?" *Journal of Finance*, 65 (2010), 861-889

Schoar, A. and L. Zuo. "Shaped by booms and busts: How the economy impacts CEO careers and management styles." *Review of Financial Studies*, 30 (2017), 1425-1456.

Shleifer, A. and R. W. Vishny. "A survey of corporate governance." *Journal of Finance*, 52 (1997), 737-783.

Skrastins, J. and V. Vig. "How organizational hierarchy affects information production." *Review of Financial Studies*, 32 (2019), 564-604.

Stein, J. C. "Information production and capital allocation: Decentralized versus hierarchical firms." *Journal of Finance*, 57 (2002), 1891-1921.

Sunder, J.; S. V. Sunder; and J. Zhang. "Pilot CEOs and corporate innovation." *Journal of Financial Economics*, 126 (2017), 543-562.

Vaske, J. J. and K. C. Kobrin. "Place attachment and environmentally responsible behavior." *Journal of Environmental Education*, 32 (2001), 16-21.

Weisbach, M. B. "Outside directors and CEO turnover." *Journal of Financial Economics*, 20 (1988), 431-460.

Yonker, S. E. "Do managers give hometown labor an edge?" *Review of Financial Studies*, 30 (2017a), 3581-3604.

Yonker, S. E. "Geography and the market for CEOs." *Management Science*, 63 (2017b), 609-630.

Table 1. Summary Statistics

This table reports summary statistics for bank and loan characteristics in the sample. Refer to Appendix 1 for the definition and construction of variables used in this study.

Panel A: Bank-county-level Statistics

Variables	N	Mean	Std.	p1	p50	p99
Key Explanatory Variables						
ln(DIST_HOMETOWN)	291,412	7.025	0.861	4.526	7.130	8.304
ln(DIST_HQ)	291,412	6.855	1.116	3.672	7.064	8.333
DIST_HOMETOWN	291,412	1,503	1,042	91.420	1,248	4,040
DIST_HQ	291,412	1,457	1,142	38.330	1,168	4,160
Key Dependent Variables						
ln(MORTGAGE_LOANS)	291,412	5.666	3.305	0.000	6.180	11.090
MORTGAGE_GROWTH	225,333	-0.049	0.354	-1.000	-0.003	0.684
APPROVAL_RATE	273,792	0.603	0.290	0.000	0.667	1.000
ln(BRANCHES)	291,412	0.237	0.630	0.000	0.000	3.045
ln($\sigma_{LOAN\ AMOUNT}$)	265,072	4.055	0.991	1.257	4.094	6.715
ln(IQR)	289,276	3.780	1.440	0.000	4.143	6.211
RESIDUAL_LOAN_AMOUNT	200,046	1.030	0.884	0.008	0.805	3.938
Loan Characteristics						
%FEMALE_APPLICANTS	291,412	0.201	0.192	0.000	0.191	1.000
%NON_WHITE_APPLICANTS	291,412	0.373	0.324	0.000	0.286	1.000
LOAN_TO_INCOME	291,412	1.401	0.722	0.183	1.359	3.757
ln(APPLICANT_INCOME)	291,412	4.297	0.536	3.157	4.247	6.088
LOAN (‘000)	291,412	121.700	190.800	8.000	92.620	606.400
INCOME (‘000)	291,412	88.490	124.400	22.500	68.870	439.700

Panel B: Bank-level Statistics

Variables	N	Mean	Std.	p1	p50	p99
CEO Characteristics						
HOMETOWN_UG	823	0.445	0.497	0.000	0.000	1.000
POWERFUL_CEO	811	0.941	0.691	0.000	1.000	2.000
Bank Characteristics						
ASSETS	906	0.002	0.010	0.000	0.000	0.055
LEVERAGE	906	15.470	2.085	12.230	15.030	21.330
ROA	906	0.907	0.029	0.801	0.910	0.953
TOTAL_LOANS	906	0.760	1.155	-5.297	0.937	2.486
DEPOSITS	906	0.660	0.131	0.256	0.680	0.883
MORTGAGE_LOANS	903	0.008	0.028	-0.085	0.009	0.078
BAD_LOANS	906	0.730	0.110	0.364	0.747	0.901
STOCK_RETS	845	0.082	0.992	0.000	0.015	0.157
%MORTGAGE_LOAN_HOMETOWN_COUNTY	906	0.448	0.161	0.044	0.459	0.776

Table 2. Proximity to CEO Hometown and Bank Lending and Branching

This table reports regressions which estimate the effects of distance to the bank CEO's hometown on bank lending and branching policies. Panel A reports bank-county-year regressions. The dependent variables are ln(MORTGAGE_LOANS), the natural logarithm of the nominal amount of mortgage loans originated by a bank in a county-year (Column (1)); MORTGAGE_GROWTH, the percentage change in mortgage originations by a bank in a given county relative to the prior year (Column (2)); APPROVAL_RATE, the number of approved mortgage loan applications divided by the total number of applications received (Column (3)); and ln(BRANCHES), the natural logarithm of the number of branches a bank has in a county in a year (Column (4)). ln(DIST_HOMETOWN) is the natural logarithm of the distance between the bank CEO's hometown county and the county in which lending or branching decisions take place. Panel B reports loan-level regression results. The dependent variable is APPROVED, a dummy variable that equals one if a loan is approved and zero otherwise. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Panel A: Bank-county-year regressions

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE	ln(BRANCHES)
	(1)	(2)	(3)	(4)
ln(DIST_HOMETOWN)	-0.119***	-0.008***	-0.015***	-0.028***
	[-15.228]	[-7.059]	[-19.170]	[-11.186]
ln(DIST_HQ)	-0.828***	-0.027***	-0.023***	-0.238***
	[-111.687]	[-30.234]	[-37.255]	[-98.392]
ASSETS	1.069***	0.099***	-0.054***	0.211***
	[37.296]	[19.430]	[-17.278]	[32.650]
LEVERAGE	-8.884***	-2.519***	-1.357***	-1.682***
	[-16.730]	[-26.631]	[-22.666]	[-14.386]
ROA	0.091***	0.018***	0.006***	0.011***
	[8.847]	[11.428]	[5.620]	[4.246]
TOTAL_LOANS	2.442***	0.281***	-0.136***	-0.03
	[20.400]	[12.340]	[-10.245]	[-1.089]
DEPOSITS	3.713***	-0.133***	0.604***	0.225***
	[30.183]	[-6.218]	[44.796]	[8.443]
%FEMALE_APPLICANTS	-0.033	-0.028***	-0.074***	-
	[-0.821]	[-3.123]	[-15.428]	-
%NON_WHITE_APPLICANTS	-2.261***	-0.170***	-0.163***	-
	[-88.311]	[-30.039]	[-51.415]	-
LOAN_TO_INCOME	0.111***	0.028***	0.036***	-
	[10.091]	[12.563]	[28.666]	-
ln(APPLICANT_INCOME)	0.574***	0.125***	0.125***	-
	[32.647]	[34.505]	[60.400]	-
County-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R-squared	0.617	0.328	0.468	0.358
Observations	291,412	222,552	273,379	291,412

Panel B: Loan-level regressions

Dependent Variable: APPROVED				
	(1)	(2)	(3)	(4)
ln(DIST_HOMETOWN)	-0.014***	-0.018***	-0.020***	-0.023***
	[-8.626]	[-11.468]	[-17.729]	[-21.516]
ln(DIST_HQ)	-0.006***	-0.004**	0.008***	0.009***
	[-3.570]	[-2.342]	[7.037]	[7.572]
ASSETS	0.002***	0.006***	-0.057***	-0.050***
	[3.027]	[7.490]	[-24.391]	[-24.476]
LEVERAGE	0.150***	0.179***	0.216***	0.234***
	[14.153]	[15.508]	[12.534]	[16.188]
ROA	0.285***	0.331***	0.234***	0.294***
	[15.905]	[17.611]	[16.032]	[21.733]
TOTAL_LOANS	0.727***	0.412***	-0.856***	-0.816***
	[14.208]	[8.778]	[-13.524]	[-13.803]
DEPOSITS	0.006***	-0.011***	0.006***	-0.002**
	[5.358]	[-10.547]	[4.453]	[-1.991]
FEMALE	-0.030***	-0.030***	-0.022***	-0.023***
	[60.429]	[65.883]	[51.850]	[58.054]
AFRICAN_AMERICAN	-0.165***	-0.161***	-0.158***	-0.155***
	[-90.932]	[-121.264]	[-109.461]	[-134.846]
ASIAN	-0.015***	-0.027***	-0.026***	-0.032***
	[-6.675]	[-19.443]	[-13.479]	[-21.777]
OTHE_RACES	-0.143***	-0.138***	-0.135***	-0.128***
	[-96.644]	[-102.627]	[-95.262]	[-99.806]
LOAN_TO_INCOME	0.002***	0.001***	0.001***	0.001***
	[9.185]	[8.321]	[8.071]	[6.649]
ln(APPLICANT_INCOME)	0.108***	0.101***	0.104***	0.098***
	[139.071]	[151.305]	[158.385]	[180.241]
County-year FE	No	Yes	No	Yes
Bank FE	No	No	Yes	Yes
R-squared	0.070	0.086	0.101	0.114
Observations	37,946,045	37,946,022	37,946,045	37,946,022

Table 3. CEO's Degree of Hometown Bias

This table reports bank-county-year regressions which estimate whether the effects of distance to the bank CEO's hometown on bank lending and branching policies are stronger for CEOs that spend more time in their hometowns. The dependent variables are ln(MORTGAGE_LOANS), the natural logarithm of the nominal amount of mortgage loans originated by a bank in a county-year (Column (1)); MORTGAGE_GROWTH, the percentage change in mortgage originations by a bank in a given county relative to the prior year (Column (2)); APPROVAL_RATE, the number of approved mortgage loan applications divided by the total number of applications received (Column (3)); and ln(BRANCHES), the natural logarithm of the number of branches a bank has in a county in a year (Column (4)). ln(DIST_HOMETOWN) is the natural logarithm of the distance between the bank CEO's hometown county and the county in which lending or branching decisions take place. HOMETOWN_UG is a dummy that equals one if the CEO undertakes an undergraduate degree in the same state as her birth state. Control variables include: ASSETS, LEVERAGE, ROA, TOTAL_LOANS, DEPOSITS, %FEMALE_APPLICANTS, %NON_WHITE_APPLICANTS, LOAN_TO_INCOME and ln(APPLICANT_INCOME). Standard errors are clustered at the county-year level. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE	ln(BRANCHES)
	(1)	(2)	(3)	(4)
HOMETOWN_UG x ln(DIST_HOMETOWN)	-0.483***	-0.016***	-0.013***	-0.082
	[-2.764]	[-6.742]	[-8.113]	[-1.268]
HOMETOWN_UG x ln(DIST_HQ)	0.237	-0.007***	0.018***	0.063*
	[1.381]	[-3.943]	[13.809]	[1.954]
ln(DIST_HOMETOWN)	0.119	-0.003*	-0.007***	0.018
	[0.820]	[-1.942]	[-6.172]	[0.373]
ln(DIST_HQ)	-0.975***	-0.025***	-0.033***	-0.274***
	[-6.096]	[-18.697]	[-33.926]	[-11.281]
HOMETOWN_UG	1.042	0.096***	-0.103***	0.151
	[0.603]	[5.306]	[-8.506]	[0.277]
Control variables	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R-squared	0.621	0.33	0.453	0.359
Observations	290,253	221,726	272,411	290,253

Table 4. Exogenous and Internal CEO Turnovers

This table reports regressions which estimate the effect of distance to the bank CEO's hometown on bank lending and branching policies around CEO turnover events. Panel A focuses on exogenous CEO turnover events. A turnover is considered to be exogenous if it arises from CEO's death, long-term illness, long-planned retirements, or if the turnover takes place when the CEO is at least 60 years of age. Panel B focuses on internal CEO turnover events, which occurs when the incoming CEO was already employed by the bank. Across both panels, the dependent variables are Δln(MORTGAGE_LOANS), the mortgage origination volume one year after the turnover minus the mortgage origination volume one year before the turnover (Column (1)); ΔMORTGAGE_GROWTH, the mortgage origination growth one year after the turnover minus the mortgage origination growth one year before the turnover (Column (2)); ΔAPPROVAL_RATE, the mortgage approval rate one year after the turnover minus the mortgage approval rate one year before the turnover (Column (3)); and Δln(BRANCHES), the number of branches one year after the turnover minus the number of branches one year before the turnover (Column (4)). The main explanatory variable ln(DIST_HOMETOWN) is the change in the proximity to CEOs' hometown resulting from the turnover. Control variables are collapsed for brevity. Control variables include: ΔASSETS, ΔLEVERAGE, ΔROA, ΔTOTAL_LOANS, ΔDEPOSITS, Δ%FEMALE_APPLICANTS, Δ%NON_WHITE_APPLICANTS, ΔLOAN_TO_INCOME, and Δln(APPLICANT_INCOME). Standard errors are clustered at the county-year level. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Panel A: Exogenous Turnovers

Dependent Variables	Δln(MORTGAGE_LOANS)	ΔMORTGAGE_GROWTH	ΔAPPROVAL_RATE	Δln(BRANCHES)
	(1)	(2)	(3)	(4)
Δln(DIST_HOMETOWN)	-0.237***	-0.023**	-0.015**	-0.012***
	[-5.220]	[-2.047]	[-2.081]	[-4.290]
Control variables	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
R-squared	0.833	0.896	0.841	0.694
Observations	12,374	9,339	11,899	12,446

Panel B: Internal Turnovers

Dependent Variables	Δln(MORTGAGE_LOANS)	ΔMORTGAGE_GROWTH	ΔAPPROVAL_RATE	Δln(BRANCHES)
	(1)	(2)	(3)	(4)
Δln(DIST_HOMETOWN)	-0.261***	-0.027**	-0.015*	-0.012***
	[-5.384]	[-2.249]	[-1.931]	[-4.293]
Control variables	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
R-squared	0.829	0.885	0.842	0.671
Observations	12,194	9,183	11,297	12,290

Table 5. The Influence of CEOs on Hometown Lending and Branching

This table reports bank-county-year regressions which estimate the effects of distance to the bank CEO's hometown on bank lending and branching policies. The dependent variables are ln(MORTGAGE_LOANS), the natural logarithm of the nominal amount of mortgage loans originated by a bank in a county-year (Column (1)); MORTGAGE_GROWTH, the percentage change in mortgage originations by a bank in a given county relative to the prior year (Column (2)); APPROVAL_RATE, the number of approved mortgage loan applications divided by the total number of applications received (Column (3)); and ln(BRANCHES), the natural logarithm of the number of branches a bank has in a county in a year (Column (4)). ln(DIST_HOMETOWN) is the natural logarithm of the distance between the bank CEO's hometown county and the county in which lending or branching decisions take place. Panel A interacts ln(DIST_HOMETOWN) with DISASTER_SEVERITY, the number of fatalities divided by the county population. Panel B interacts ln(DIST_HOMETOWN) with POWERFUL_CEO, the sum of two dummy variables on whether the fraction of outside directors on the board is below the sample median and whether the CEO's tenure is above the sample median. Control variables are collapsed for brevity. Control variables include: ASSETS, LEVERAGE, ROA, TOTAL_LOANS, DEPOSITS, %FEMALE_APPLICANTS, %NON_WHITE_APPLICANTS, LOAN_TO_INCOME and ln(APPLICANT_INCOME). Standard errors are clustered at the county-year level. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Panel A: Disaster Lending

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE	ln(BRANCHES)
	(1)	(2)	(3)	(4)
DISASTER_SEVERITY x ln(DIST_HOMETOWN)	-0.026***	-0.003**	-0.001	-0.018***
	[-2.848]	[-2.116]	[-0.626]	[-5.956]
DISASTER_SEVERITY x ln(DIST_HQ)	0.070***	0.005***	0.002***	-0.007***
	[9.210]	[5.791]	[2.862]	[-2.773]
ln(DIST_HOMETOWN)	-0.103***	-0.007***	-0.014***	-0.017***
	[-11.105]	[-4.609]	[-15.383]	[-6.628]
ln(DIST_HQ)	-0.871***	-0.030***	-0.025***	-0.234***
	[-102.597]	[-28.349]	[-32.939]	[-87.567]
Control variables	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R-squared	0.617	0.328	0.468	0.358
Observations	291,412	222,552	273,379	291,412

Panel B: CEO Power

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE	ln(BRANCHES)
	(1)	(2)	(3)	(4)
POWERFUL_CEO x ln(DIST_HOMETOWN)	-0.026**	-0.008***	-0.001	-0.031***
	[-2.460]	[-4.896]	[-0.753]	[-9.976]
POWERFUL_CEO x ln(DIST_HQ)	0.008	0.007***	-0.012***	0.017***
	[0.908]	[5.439]	[-14.536]	[6.169]
ln(DIST_HOMETOWN)	-0.105***	-0.009***	-0.011***	-0.006*
	[-9.578]	[-5.492]	[-10.392]	[-1.745]
ln(DIST_HQ)	-0.828***	-0.029***	-0.013***	-0.252***
	[-80.852]	[-24.570]	[-15.745]	[-76.537]
POWERFUL_CEO	0.195***	0.081***	0.079***	0.098***
	[3.092]	[7.821]	[12.012]	[5.304]
Control variables	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R-squared	0.617	0.331	0.471	0.357
Observations	272,942	206,821	256,315	272,942

Table 6. Loan Performance

This table reports loan-level regressions which estimate the effect of distance to the bank CEO's hometown on ex-post loan performance. The dependent variable is LOAN_DELINQUENCIES, a dummy variable equals one if a loan becomes 90 days delinquent or enters foreclosure during the first two years of its life. ln(DIST_HOMETOWN) is the natural logarithm of the distance between the bank CEO's hometown county and the county in which lending or branching decisions take place. All models include county-year and bank fixed effects. Standard errors are clustered at the county-year level. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Dependent Variables: LOAN_DELINQUENCIES			
	(1)	(2)	(3)
ln(DIST_HOMETOWN)	0.00123**	0.00133**	0.00113**
	[2.108]	[2.305]	[1.986]
ln(DIST_HQ)	-0.001*	-0.001*	0.000
	[-1.753]	[-1.653]	[-1.107]
ASSETS		-0.003	-0.003
		[-0.765]	[-0.652]
LEVERAGE		0.211***	0.154***
		[3.987]	[2.900]
ROA		-0.001	-0.001
		[-1.047]	[-1.057]
TOTAL_LOANS		-0.013	-0.016
		[-0.815]	[-1.065]
DEPOSITS		0.008	0.006
		[0.540]	[0.384]
FEMALE			0.001
			[1.171]
AFRICAN_AMERICAN			0.002
			[1.039]
ASIAN			-0.002
			[-1.144]
OTHER_RACES			-0.002*
			[-1.680]
LOAN_TO_INCOME			0.003
			[1.605]
ln(APPLICANT_INCOME)			0.003
			[1.107]
LOAN_TO_VALUE			0.000***
			[12.751]
FICO			-0.000***
			[-28.268]
County-year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
R-squared	0.099	0.099	0.114
Observations	165,459	163,508	162,875

Table 7. Contract Dispersion

This table reports bank-county-year regressions which estimate the effect of distance to the bank CEO's hometown on the dispersion of contractual terms. The dependent variables are ln(σ_{LOAN_AMOUNT}), the natural logarithm of the standard deviation of the amount of loans originated by a bank in a county-year (Column (1)); ln(IQR), the natural logarithm of the interquartile range of the amount of loans originated by a bank in a county-year (Column (2)); and RESIDUAL_LOAN_AMOUNT, the residual in the regressions of observable borrower and loan characteristics on ln(LOAN_AMOUNT) (Column (3)). ln(DIST_HOMETOWN) is the natural logarithm of the distance between the bank CEO's hometown county and the county in which lending or branching decisions take place. Standard errors are clustered at the county-year level. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Dependent Variables	ln(σ_{LOAN_AMOUNT})	ln(IQR)	RESIDUAL_LOAN_AMOUNT
	(1)	(2)	(3)
ln(DIST_HOMETOWN)	-0.039***	-0.026***	-0.021***
	[-18.485]	[-6.761]	[-5.614]
ln(DIST_HQ)	-0.131***	-0.236***	-0.064***
	[-71.857]	[-68.790]	[-19.290]
ASSETS	0.221***	0.354***	-0.018
	[25.880]	[21.997]	[-1.246]
LEVERAGE	1.870***	-0.953***	1.682***
	[11.959]	[-3.218]	[6.846]
ROA	0.012***	0.009	0.027***
	[4.230]	[1.557]	[4.983]
TOTAL_LOANS	0.635***	0.847***	-0.260***
	[16.728]	[12.709]	[-4.718]
DEPOSITS	-0.034	0.642***	0.317***
	[-1.028]	[9.805]	[4.782]
%FEMALE_APPLICANTS	0.087***	0.011	-
	[6.143]	[0.426]	-
%NON_WHITE_APPLICANTS	-0.118***	-0.345***	-
	[-14.073]	[-21.239]	-
LOAN_TO_INCOME	0.704***	0.448***	-
	[167.996]	[63.098]	-
ln(APPLICANT_INCOME)	0.969***	0.885***	-
	[140.735]	[76.640]	-
County-year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
R-squared	0.708	0.472	0.364
Observations	264,166	289,254	200,046

Table 8. CEO Hometown Lending and Bank Performance

This table reports bank-level regressions which estimate the relationship between the proportion of mortgage lending in the CEO's hometown county and various measures of bank performance. The dependent variables are TOTAL_LOANS, total loans divided by total assets (Column (1)); MORTGAGE_LOANS, total mortgage loans divided by total assets (Column (2)); BAD_LOANS, bad loans divided by mortgage loans (Column (3)); ROA, net income divided by total assets (Column (4)); and STOCK_RETS, (closing stock prices minus opening stock prices) divided by opening stock prices (Column (5)). %MORTGAGE_LOAN_HOME_COUNTY is a bank's proportion of mortgage lending made in the CEO's birth county. Standard errors are clustered at the bank level. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Dependent Variables:	TOTAL_LOANS	MORTGAGE_LOANS	BAD_LOANS	ROA	STOCK_RETS
	(1)	(2)	(3)	(4)	(5)
%MORTGAGE_LOAN_HOME_COUNTY	0.046	0.263	-2.557	1.636	-0.158
	[0.188]	[1.401]	[-0.972]	[0.609]	[-1.611]
ASSETS	-0.009	0.014	0.037	0.107	-0.010***
	[-0.523]	[1.335]	[1.075]	[0.519]	[-2.902]
LEVERAGE	-0.128	0.149	1.645	-18.572***	0.023
	[-0.580]	[1.162]	[0.944]	[-3.995]	[0.386]
ROA	0.000	0.001	0.000	-	0.008***
	[-0.086]	[0.717]	[0.040]	-	[8.407]
TOTAL_LOANS	-	0.736***	-0.431	-0.071	-0.014
	-	[12.930]	[-1.064]	[-0.085]	[-0.936]
DEPOSITS	0.109	-0.017	-0.246	-1.714	0.000
	[1.024]	[-0.368]	[-0.836]	[-1.472]	[-0.007]
Year FE	Yes	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes	Yes
R-squared	0.177	0.643	0.035	0.274	0.390
Observations	906	906	845	906	903

Table 9. CEO's Hometown Lending and Borrower Characteristics

This table reports bank-county-year regressions which estimate the effect of distance to the bank CEO's hometown on bank lending and branching policies conditional on applicant characteristics. The dependent variables are ln(MORTGAGE_LOANS), the natural logarithm of the nominal amount of mortgage loans originated by a bank in a county-year; MORTGAGE_GROWTH, the percentage change in mortgage originations by a bank in a given county relative to the prior year; and APPROVAL_RATE, the number of approved mortgage loan applications divided by the total number of applications received. ln(DIST_HOMETOWN) is the natural logarithm of the distance between the bank CEO's hometown county and the county in which lending or branching decisions take place. Panel A interacts ln(DIST_HOMETOWN) with LOW_INCOME_APPLICANTS, a dummy that equals one if the applicant income is below the sample median and zero otherwise. Panel B interacts ln(DIST_HOMETOWN) with %NON_WHITE_APPLICANTS. Panel C interacts ln(DIST_HOMETOWN) with %FEMALE_APPLICANTS. Control variables are collapsed for brevity. Control variables include: ASSETS, LEVERAGE, ROA, TOTAL_LOANS, DEPOSITS, LOAN_TO_INCOME, ln(APPLICANT_INCOME), %FEMALE_APPLICANTS and %NON_WHITE_APPLICANTS. Standard errors are clustered at the county-year level. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Panel A: Lending to Low Income Applicants

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE
	(1)	(2)	(3)
LOW_INCOME_APPLICANTS x ln(DIST_HOMETOWN)	0.022	-0.004*	-0.008***
	[1.596]	[-1.844]	[-5.642]
LOW_INCOME_APPLICANTS x ln(DIST_HQ)	-0.230***	0.003**	-0.002*
	[-21.758]	[2.074]	[-1.765]
ln(DIST_HOMETOWN)	-0.114***	-0.007***	-0.011***
	[-11.872]	[-5.357]	[-12.542]
ln(DIST_HQ)	-0.732***	-0.027***	-0.022***
	[-88.625]	[-27.406]	[-31.384]
Control variables	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
R-squared	0.618	0.329	0.469
Observations	291,412	222,552	273,379

Panel B: Lending to Non-White Applicants

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE
	(1)	(2)	(3)
%NON_WHITE_APPLICANTS x ln(DIST_HOMETOWN)	-0.206***	-0.022***	0.003
	[-7.756]	[-4.642]	[1.176]
%NON_WHITE_APPLICANTS x ln(DIST_HQ)	0.108***	0.011***	0.003
	[4.830]	[2.770]	[1.168]
ln(DIST_HOMETOWN)	-0.041***	0.000	-0.016***
	[-3.168]	[-0.156]	[-12.403]
ln(DIST_HQ)	-0.863***	-0.031***	-0.025***
	[-83.447]	[-20.046]	[-24.010]
Control variables	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
R-squared	0.617	0.328	0.468
Observations	291,412	222,552	273,379

Panel C: Lending to Female Applicants

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE
	(1)	(2)	(3)
%FEMALE_APPLICANTS x ln(DIST_HOMETOWN)	-0.069*	-0.012*	-0.021***
	[-1.950]	[-1.721]	[-3.469]
%FEMALE_APPLICANTS x ln(DIST_HQ)	0.452***	0.021***	0.029***
	[15.011]	[3.636]	[5.844]
ln(DIST_HOMETOWN)	-0.102***	-0.006***	-0.010***
	[-9.853]	[-2.878]	[-6.740]
ln(DIST_HQ)	-0.926***	-0.032***	-0.030***
	[-102.056]	[-19.293]	[-23.194]
Control variables	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
R-squared	0.617	0.328	0.468
Observations	291,412	222,552	273,379

Table 10. Proximity to CEO Hometown and Small Business Lending

This table reports bank-county-year regressions which estimate the effect of distance to the bank CEO's hometown on small business lending. The dependent variable is ln(SMALL_BUSINESS_LOANS), the natural logarithm of the nominal amount of small business loans originated by a bank in a county-year. Column (1) includes loans whose amount at origination is less than or equal to $100,000. Column (2) includes loans whose amount at origination is more than $100,000 but less than or equal to $250,000. Column (3) includes loans whose amount at origination is more than $250,000 but less than or equal to $1,000,000. ln(DIST_HOMETOWN) is the natural logarithm of the distance between the bank CEO's hometown county and the county in which lending or branching decisions take place. Standard errors are clustered at the county-year level. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Loan size	Amount <=$100k	100k<Amount <=$250k	250k<Amount <=$1000k
Dependent variable:	ln(SMALL_BUSINESS_LOANS)		
	(1)	(2)	(3)
ln(DIST_HOMETOWN)	-0.642***	-0.310***	0.072
	[-15.559]	[-5.013]	[1.054]
ln(DIST_HQ)	-1.490***	-1.300***	-0.919***
	[-35.881]	[-21.135]	[-13.744]
ASSETS	0.107***	0.032***	-0.036***
	[18.299]	[3.723]	[-3.724]
LEVERAGE	1.406***	0.905***	0.618***
	[48.538]	[20.869]	[13.250]
ROA	-1.797***	-0.053	-1.072
	[-3.816]	[-0.072]	[-1.319]
TOTAL_LOANS	-0.065***	0.002	-0.031*
	[-6.100]	[0.118]	[-1.730]
DEPOSITS	1.660***	1.662***	0.209
	[15.373]	[9.141]	[1.021]
County-year FE	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes
R-squared	0.585	0.491	0.499
Observations	217,861	217,861	217,861

Appendix 1. Variable Construction and Definitions

Variable	Definition	Source
Key Explanatory Variables		
ln(DIST_HOMETOWN)	The natural logarithm of the physical distance between the bank CEO's hometown county and the county in which lending or branching decisions take place	Various sources
ln(DIST_HQ)	The natural logarithm of the physical distance between the bank HQ county and the county in which lending or branching decisions take place	SOD
HOMETOWN_STATE	A dummy that equals one if the CEO's birth state and the state in which the lending or branching decisions take place is the same	Various sources
HQ_STATE	A dummy that equals one if the bank's HQ state and the state in which the lending or branching decisions take place is the same	SOD
Bank Characteristics		
ASSETS	Natural logarithm of total assets	FR Y-9C
LEVERAGE	Total liabilities divided by total assets	FR Y-9C
ROA	Earnings before interest and taxes divided by total assets	FR Y-9C
TOTAL_LOANS	Total loans divided by total assets	FR Y-9C
MORTGAGE_LOANS	Mortgage loans divided by total assets	FR Y-9C
DEPOSITS	Total deposits divided by total assets	FR Y-9C
BAD_LOANS	Bad loans divided by total mortgage loans	FR Y-9C
STOCK_RETS	(Closing stock prices minus opening stock prices) divided by opening stock prices	CRSP
%MORTGAGE_LOAN_HOME_COUNTY	The fraction of a bank's mortgage lending originated in the bank CEO's birth county	HMDA
BOARD_INDEPENDENCE	The fraction of outside directors on the board	BoardEx
G_INDEX	Index of governance provisions developed by Gompers, Ishii, and Matrick (2003)	Riskmetrics
Mortgage Loan Variables		
ln(MORTGAGE_LOANS)	The natural logarithm of the nominal amount of mortgage loans originated by a bank in a county-year	HMDA
MORTGAGE_GROWTH	The percentage change in mortgage originations by a bank in a given county relative to the prior year	HMDA
APPROVAL_RATE	The number of approved mortgage loan applications divided by the total number of applications received	HMDA
ln(BRANCHES)	The natural logarithm of the number of branches a bank has in a county in a year	HMDA
ln(σ_{LOAN_AMOUNT})	The natural logarithm of the standard deviation of the amount of loans originated by a bank in a county-year	HMDA
ln(IQR)	The natural logarithm of the interquartile range of the amount of loans originated by a bank in a county-year	HMDA
RESIDUAL_LOAN_AMOUNT	The residual in the regressions of observable borrower and loan characteristics on ln(LOAN_AMOUNT). The dependent variable is ln(LOAN_AMOUNT), the natural logarithm of the loan amount of loans originated in a given bank-county-year. The explanatory variables are %FEMALE_APPLICANTS, %NON_WHITE_APPLICANTS, ln(APPLICANT_INCOME), %CONVENTIONAL_LOANS, %OCCUPIED_HOMES, and %REFINANCING.	HMDA
LOAN_DELINQUENCIES	A dummy that equals one if an approved loan becomes 90-day delinquent or enter foreclosure during the first two years of a loan's life	Fannie Mae
%FEMALE_APPLICANTS	The ratio of the number of applications from female applicants to the total number of applications reviewed for each bank-county-year.	HMDA
%NON_WHITE_APPLICANTS	The ratio of the number of applications from non-white applicants to the total number of applications reviewed for each bank-county-year. Non-white applicants include all applicants whose reported race is non-white	HMDA
LOAN_TO_INCOME	The average ratio of the loan amount in a mortgage application to the applicant's income for applications reviewed in each bank-county-year	HMDA
LOW_INCOME_APPLICANTS	A dummy that equals one if the income of mortgage applicants received in a bank-county-year is below the sample median	HMDA
APPROVED	A dummy that equals one if a loan is approved	HMDA
FEMALE	A dummy that equals one if the applicant is female	HMDA
AFRICAN_AMERICAN	A dummy that equals one if the applicant is an African American	HMDA
ASIAN	A dummy that equals one if the applicant is Asian	HMDA
OTHER_RACES	A dummy that equals one if the applicant is American Indian, Alaska Native, Native Hawaiian, or Other Pacific Islander	HMDA
LOAN_TO_VALUE	Loan amount to property value of approved loans	Fannie Mae
FICO	FICO score of approved loans	Fannie Mae
Small Business Loan Variables		
ln(SMALL BUSINESS LOANS)	The natural logarithm of the nominal amount of small business loans originated by a bank in a county-year	CRA

County-level Variables		
DISASTER_SEVERITY	The number of fatalities divided by the county population	SHELDUS
CEO's Characteristics		
HOMETOWN_UG	A dummy that equals one if the CEO undertakes an undergraduate degree in her birth state	BoardEx
POWERFUL_CEO	The sum of two dummy variables on whether the fraction of outside directors on the board is below the sample median and whether the CEO's tenure is above the sample median.	BoardEx
MBA	A dummy that equals one if the CEO has an MBA degree	BoardEx
IVY_LEAGUE	A dummy that equals one if the CEO obtains a degree from an Ivy League institution	BoardEx
AGE	The age of the CEO	BoardEx
DEPRESSION_BABY	A dummy that equals one if the CEO is born between 1920 and 1929	BoardEx
CRISIS_CAREER_STARTER	A dummy that equals one if the CEO starts her career (assuming at the age of 22) during a crisis	BoardEx, NBER crisis database
OVERCONFIDENCE	A dummy that equals one if the CEO holds exercisable stock options that are at least 67% in the money.	BoardEx
MILITARY_EXPERIENCE	A dummy that equals one if the CEO has prior military experience	BoardEx
CASH_PAY	CEO's salary + bonus divided by total compensation (TDC1)	ExecuComp
VEGA_SCALED	vega divided by cash pay (salary + bonus)	ExecuComp
DELTA_SCALED	delta divided by cash pay (salary + bonus)	ExecuComp

Appendix 2. CEO's Birth State

This table reports descriptive statistics of states in which bank CEOs were born in. The sample covers the period 1999–2014 for which data on CEOs' birth counties are available.

Birth State	Number of Non-local CEOs	Total Number of CEOs
Alabama (AL)	2	13
Arkansas (AR)	0	2
Arizona (AZ)	2	3
California (CA)	7	27
Connecticut (CT)	3	10
District of Columbia (DC)	2	2
Florida (FL)	2	10
Georgia (GA)	2	13
Hawaii (HI)	0	3
Iowa (IA)	2	6
Illinois (IL)	11	20
Indiana (IN)	12	19
Kansas (KS)	2	4
Kentucky (KY)	1	7
Louisiana (LA)	0	3
Massachusetts (MA)	6	17
Maryland (MD)	2	9
Maine (ME)	1	8
Michigan (MI)	5	11
Minnesota (MN)	4	7
Missouri (MO)	2	8
Mississippi (MS)	8	19
Montana (MT)	1	2
North Carolina (NC)	8	31
North Dakota (ND)	0	1
Nebraska (NE)	2	2
New Jersey (NJ)	2	16
New York (NY)	18	48
Ohio (OH)	13	25
Oklahoma (OK)	1	3
Oregon (OR)	0	2
Pennsylvania (PA)	13	48
Rhode Island (RI)	3	4
South Carolina (SC)	5	13
South Dakota (SD)	2	2
Tennessee (TN)	0	2
Texas (TX)	9	18
Utah (UT)	1	3
Virginia (VA)	10	24
Vermont (VT)	2	3
Washington (WA)	1	8
Wisconsin (WI)	2	3
West Virginia (WV)	2	6
Total	**171**	**485**

Appendix 3. Excluding Top Three CEO Hometown States

This table reports bank-county-year regression results which estimate the effect of distance to the bank CEO's hometown on bank lending and branching policies. We exclude all loans originated by banks led by CEOs who grew up in the top three CEO hometown states: New York, Pennsylvania, and Ohio. The dependent variables are ln(MORTGAGE_LOANS), the natural logarithm of the nominal amount of mortgage loans originated by a bank in a county-year (Column (1)); MORTGAGE_GROWTH, the percentage change in mortgage originations by a bank in a given county relative to the prior year (Column (2)); APPROVAL_RATE, the number of approved mortgage loan applications divided by the total number of applications received (Column (3)) and; ln(BRANCHES), the natural logarithm of the number of branches a bank has in a county in a year (Column (4)). ln(DIST_HOMETOWN) is the natural logarithm of the distance between the bank CEO's hometown county and the county in which lending or branching decisions take place. Control variables are collapsed for brevity. Control variables include: ASSETS, LEVERAGE, ROA, TOTAL_LOANS, DEPOSITS, %FEMALE_APPLICANTS, %NON_WHITE_APPLICANTS, LOAN_TO_INCOME and ln(APPLICANT_INCOME). Standard errors are clustered at the county-year level. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE	ln(BRANCHES)
	(1)	(2)	(3)	(4)
ln(DIST_HOMETOWN)	-0.106***	-0.008***	-0.013***	-0.033***
	[-11.692]	[-5.805]	[-14.232]	[-11.199]
ln(DIST_HQ)	-0.789***	-0.022***	-0.022***	-0.250***
	[-95.108]	[-20.967]	[-30.775]	[-95.904]
Control variables	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R-squared	0.649	0.369	0.522	0.404
Observations	213,951	165,051	201,693	213,951

Appendix 4. Alternative Definitions of Hometown Proximity

This table reports bank-county-year regressions using alternative definitions of distance to a CEO's hometown. In Panel A, our main explanatory variable is HOMETOWN_STATE, a dummy variable that equals one if the CEO's birth state and the state in which the lending or branching decisions take place is in the same. In Panel B**,** we use 10 dummy variables, each equal to one if the lending and branching decisions take place within 200km, 200-400km, 400-600km, 600-800km, 800-1000km from the CEO's hometown (bank's HQ) and zero otherwise. The dependent variables are ln(MORTGAGE_LOANS), the natural logarithm of the nominal amount of mortgage loans originated by a bank in a county-year (Column (1)); MORTGAGE_GROWTH, the percentage change in mortgage originations by a bank in a given county relative to the prior year (Column (2)); APPROVAL_RATE, the number of approved mortgage loan applications divided by the total number of applications received (Column (3)); and ln(BRANCHES), the natural logarithm of the number of branches a bank has in a county in a year (Column (4)). Control variables are collapsed for brevity. Control variables include: ASSETS, LEVERAGE, ROA, TOTAL_LOANS, DEPOSITS, %FEMALE_APPLICANTS, %NON_WHITE_APPLICANTS, LOAN_TO_INCOME and ln(APPLICANT_INCOME). Standard errors are clustered at the county-year level. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Panel A: Hometown State Lending

Dependent variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE	ln(BRANCHES)
	(1)	(2)	(3)	(4)
HOMETOWN_STATE	0.756***	0.035***	0.053***	0.170***
	[26.936]	[7.696]	[17.802]	[22.428]
HQ_STATE	2.568***	0.095***	0.097***	0.573***
	[119.491]	[32.119]	[48.327]	[79.936]
Control variables	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R-squared	0.612	0.328	0.469	0.321
Observations	291,412	222,552	273,379	291,412

Panel B: Varying Distance

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_GROWTH	ln(BRANCHES)
	(1)	(2)	(3)	(4)
HOWNTOWN<200km	0.327***	0.032***	0.045***	0.048***
	[10.919]	[7.126]	[14.864]	[5.562]
200km<HOMEOWN<400km	0.361***	0.033***	0.030***	0.046***
	[16.851]	[9.929]	[13.405]	[8.263]
400km<HOMETOWN<600km	0.335***	0.040***	0.014***	0.077***
	[17.614]	[13.066]	[6.975]	[16.682]
600km<HOMETOWN<800km	0.100***	0.023***	0.008***	0.023***
	[5.431]	[7.250]	[3.913]	[5.243]
800km<HOMETOWN<1000km	-0.023	0.009***	0.004*	-0.013***
	[-1.272]	[2.898]	[1.946]	[-3.158]
HQ<200km	2.871***	0.093***	0.098***	0.680***
	[112.498]	[25.899]	[39.928]	[84.851]
200km<HQ<400km	1.435***	0.044***	0.036***	0.350***
	[70.339]	[14.179]	[16.994]	[65.780]
400km<HQ<600km	0.871***	0.022***	0.023***	0.249***
	[44.586]	[6.963]	[11.260]	[51.205]
600km<HQ<800km	0.357***	0.010***	0.016***	0.126***
	[18.040]	[2.904]	[7.422]	[26.360]
800km<HQ<1000km	0.268***	-0.004	-0.005**	0.185***
	[14.293]	[-1.136]	[-2.235]	[37.600]
Control variables	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R-squared	0.617	0.329	0.469	0.332
Observations	291,412	222,552	273,379	291,412

Appendix 5. Controlling for CEO Characteristics and Bank Corporate Governance

This table reports bank-county-year regressions which estimate the effect of distance to the bank CEO's hometown on bank lending and branching policies. The dependent variables are ln(MORTGAGE_LOANS), the natural logarithm of the nominal amount of mortgage loans originated by a bank in a county-year (Column (1)); MORTGAGE_GROWTH, the percentage change in mortgage originations by a bank in a given county relative to the prior year (Column (2)); APPROVAL_RATE, the number of approved mortgage loan applications divided by the total number of applications received (Column (3)); and ln(BRANCHES), the natural logarithm of the number of branches a bank has in a county in a year (Column (4)). ln(DIST_HOMETOWN) is the natural logarithm of the distance between the bank CEO's hometown county and the county in which lending or branching decisions take place. Panel A includes additional controls for observable CEO characteristics: MBA, a dummy that equals one if the CEO has an MBA degree; IVY_LEAGUE, a dummy that equals one if the CEO obtains a degree from an Ivy League institution; AGE, the age of CEO; DEPRESSION_BABY, a dummy that equals one if the CEO is born between 1930 and 1939; CRISIS_CAREER_STARTER, a dummy that equals one if the CEO starts their career (assuming at the age of 22) during a crisis period (defined according to the NBER crisis database); and OVERCONFIDENCE, a dummy variable that equals one if moneyness of the option holdings is 67% and above. Panel B includes additional controls for components of CEO pay: ln(TOTAL_COMP), the natural logarithm of the CEO's total compensation (tdc1 in ExecuComp); CASH_PAY, (salary + bonus) divided by total compensation (tdc1 in ExecuComp); VEGA_SCALED, vega divided by cash pay (salary + bonus); and DELTA_SCALED is delta divided by cash pay (salary + bonus). Panel C includes additional controls for bank governance: BOARD_INDEPENDENCE, the fraction of outside directors on the boards; G_INDEX, index of governance provisions developed by Gompers et al. (2003). Control variables are collapsed for brevity. Control variables include: ASSETS, LEVERAGE, ROA, TOTAL_LOANS, DEPOSITS, %FEMALE_APPLICANTS, %NON_WHITE_APPLICANTS, LOAN_TO_INCOME and ln(APPLICANT_INCOME). Standard errors are clustered at the county-year level. Refer to Appendix 1 for the definition and construction of variables used in this study. The constant is suppressed. *t*-statistics are reported in parentheses. ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Panel A: Controlling for Observable CEO Characteristics

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE	ln(BRANCHES)
	(1)	(2)	(3)	(4)
ln(DIST_HOMETOWN)	-0.167***	-0.011***	-0.014***	-0.040***
	[-20.403]	[-8.788]	[-16.486]	[-13.714]
ln(DIST_HQ)	-0.720***	-0.022***	-0.015***	-0.238***
	[-88.882]	[-21.079]	[-21.086]	[-81.388]
MBA	-0.662***	-0.066***	-0.042***	0.011
	[-13.445]	[-8.666]	[-7.942]	[0.886]
IVY_LEAGUE	0.323***	0.034***	0.064***	0.009
	[9.830]	[6.549]	[18.031]	[1.010]
AGE	0.014***	0.006***	-0.002***	0.001*
	[6.567]	[15.864]	[-10.231]	[1.874]
DEPRESSION_BABY	0.792***	0.099***	0.119***	0.043***
	[17.039]	[10.919]	[22.419]	[3.563]
CRISIS_CAREER_STARTER	0.174***	0.053***	0.050***	0.002
	[6.000]	[11.169]	[17.515]	[0.331]
OVERCONFIDENCE	-0.329***	-0.056***	0.016***	0.041***
	[-8.756]	[-8.485]	[4.071]	[5.384]
Control variables	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R-squared	0.659	0.360	0.487	0.377
Observations	232,449	175,682	218,814	232,449

Panel B: Controlling for CEO Pay Elements

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE	ln(BRANCHES)
	(1)	(2)	(3)	(4)
ln(DIST_HOMETOWN)	-0.174***	-0.011***	-0.015***	-0.040***
	[-21.630]	[-8.999]	[-18.125]	[-15.072]
ln(DIST_HQ)	-0.768***	-0.026***	-0.020***	-0.234***
	[-96.146]	[-26.775]	[-28.745]	[-85.286]
ln(TOTAL_COMP)	-0.169***	0.036***	-0.046***	-0.014***
	[-11.298]	[13.664]	[-26.633]	[-3.336]
CASH_PAY	-1.204***	-0.024**	-0.235***	-0.102***
	[-21.725]	[-2.514]	[-38.784]	[-7.382]
VEGA_SCALED	0.398***	-0.016***	0.011***	-0.027***
	[18.304]	[-3.799]	[4.250]	[-4.786]
DELTA_SCALED	0.195***	0.007*	0.016***	0.015***
	[10.861]	[1.804]	[7.104]	[3.305]
Control variables	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R-squared	0.647	0.354	0.490	0.373
Observations	261,239	201,220	245,126	261,239

Panel C: Controlling for Bank Corporate Governance

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE	ln(BRANCHES)
	(1)	(2)	(3)	(4)
ln(DIST_HOMETOWN)	-0.143***	-0.009***	-0.016***	-0.034***
	[-17.493]	[-7.753]	[-19.307]	[-12.385]
ln(DIST_HQ)	-0.731***	-0.023***	-0.016***	-0.233***
	[-91.126]	[-23.037]	[-23.625]	[-83.705]
BOARD_INDEPENDENCE	-0.033	-0.105***	-0.017***	0.017
	[-0.637]	[-11.478]	[-3.235]	[1.289]
G_INDEX	-0.043***	-0.012***	0	0.006***
	[-5.129]	[-7.565]	[-0.344]	[2.875]
Control variables	Yes	Yes	Yes	Yes
County-year FE	Yes	Yes	Yes	Yes
Bank FE	Yes	Yes	Yes	Yes
R-squared	0.638	0.339	0.481	0.364
Observations	253,257	193,870	238,804	253,257

Appendix 6. Using Selection on Observables to Assess Bias from Uobservables (Oster, 2019)

This table reports the results of Oster's (2019) test for the amount of variation in unobservables relative to observables needed to bring the estimated effect on ln(DIST_HOMETOWN) to zero. Following Oster (2019), δ is measured as $\frac{\beta_{Full}}{\beta_{Restrict}-\beta_{Full}}\ x\ \frac{R_{Full}-R_{Restrict}}{R_{Max}-R_{Full}}$, where $\beta_{Restrict}$ is the coefficient on ln(DIST_HOMETOWN) from the model using a restricted set of controls, β_{Full} is the coefficient on ln(DIST_HOMETOWN) from the model using a full set of controls. The restricted model does not include any fixed effects or control variables, i.e., ln(DIST_HOMETOWN) is the only explanatory variable included. The full models correspond to Columns (1)-(4) in Panel A of Table 2. Following Oster (2019), we specify $R_{Max} = 1.3R_{Full}$, where R_{Max} is the R^2 from a hypothetical regression that includes both observed and unobserved controls and R_{Full} is the R^2 from a regression that includes a full set of controls. The beta range is [β*, β_{Full}], where the bias-adjusted treatment effect is $\beta^* = \beta_{Full} - (\beta_{Restrict} - \beta_{Full})\ x\ \frac{R_{Max}-R_{Full}}{R_{Full}-R_{Restrict}}$.

Dependent Variables	**Full Model**	δ	**Beta Range**
ln(MORTGAGE_LOANS)	Control variables + County-Year FE + Bank FE	16.776	[-0.112, -0.119]
MORTGAGE_GROWTH	Control variables + County-Year FE + Bank FE	4.576	[-0.008, -0.010]
APPROVAL_RATE	Control variables + County-Year FE + Bank FE	3.994	[-0.011, -0.015]
ln(BRANCHES)	Control variables + County-Year FE + Bank FE	2.193	[-0.015, -0.028]

Appendix 7. Other Robustness Tests

Panel A presents various robustness tests on our baseline results in Panel A of Table 2. In Row (1), we perform our regressions based on a standard Heckman (1979) two-step procedure to account for potential self-selection. The first step of the Heckman procedure estimates the probability that a CEO is included in our sample. The sample in the first step includes: (1) banks led by non-local CEOs that are included in the main sample; and (2) banks that we are unable to include in the sample due to missing CEO's birth counties. The dependent variable in the first step is a dummy that equals one if a CEO is included in the sample and zero otherwise. All regression specifications include bank and county-year fixed effects and a full set of control variables: ln(DIST_HQ), ASSETS, LEVERAGE, ROA, DEPOSITS, TOTAL_LOANS, ln(APPLICANT_INCOME), LOAN_TO_INCOME, %FEMALE_APPLICANTS, and %NON_WHITE_APPLICANTS. The second step of the Heckman procedure includes LAMBDA, which contains information from the first step to control for the unobservable factors that make sample inclusion more likely. We exclude the 10% smallest banks (Row (2)); exclude the 10% largest banks (Row (3)); exclude observations covering the 2007-09 financial crisis (Row (4)); control for the staggered deregulation of interstate bank branching laws (Rice and Strahan 2010) (Row (5)); and include both local and non-local CEOs in the sample (Row (6)). Panel B reports regressions which estimate the effect of distance to the bank CEO's hometown on DEPOSIT_GROWTH, the percentage change in total deposits a bank receives in a given county relative to the prior year. For brevity, we only display the estimates and *t*-statistics for ln(DIST_HOMETOWN). ***, **, and * indicate significance at the 1, 5 and 10% level, respectively.

Panel A: Robustness Tests on Baseline Results (Panel A of Table 2)

Dependent Variables	ln(MORTGAGE_LOANS)	MORTGAGE_GROWTH	APPROVAL_RATE	ln(BRANCHES)
	(1)	(2)	(3)	(4)
(1) Heckman (1979) two-step procedure	-0.109***	-0.008***	-0.014***	-0.028***
	[-14.191]	[-7.125]	[-18.063]	[-10.891]
(2) Excluding the 10% smallest banks	-0.132***	-0.009***	-0.015***	-0.029***
	[-16.869]	[-7.628]	[-19.700]	[-11.331]
(3) Excluding the 10% largest banks	-0.073***	-0.007***	-0.007***	-0.031***
	[-8.917]	[-5.555]	[-9.009]	[-12.203]
(4) Excluding the 2007-9 financial crisis	-0.143***	-0.008***	-0.014***	-0.032***
	[-16.201]	[-6.236]	[-16.552]	[-11.829]
(5) Controlling for IBBEA deregulation	-0.134***	-0.015***	-0.008***	-0.034***
	[-12.768]	[-8.466]	[-7.037]	[-9.806]
(6) Including local and non-local CEOs	-0.258***	-0.011***	-0.017***	-0.035***
	[-42.792]	[-13.809]	[-29.227]	[-19.748]

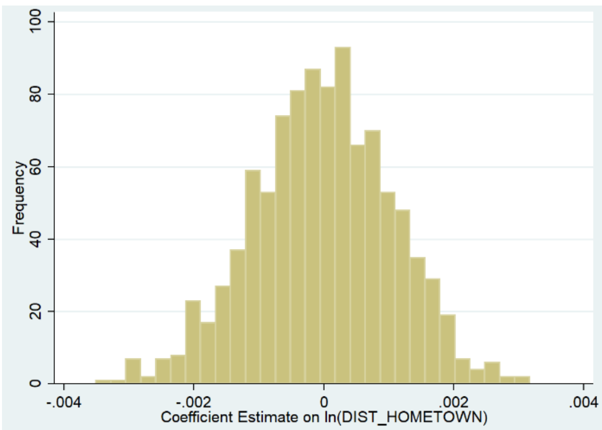
Panel B: Placebo Test on Deposit Growth

Dependent Variable	DEPOSIT_GROWTH
	(1)
ln(DIS_HOMETOWN)	-1.942
	[-0.843]
ln(DIST_HQ)	-1.582
	[-0.859]
Control variables	Yes
County-year FE	Yes
Bank FE	Yes
R-squared	0.245
Observations	30,186

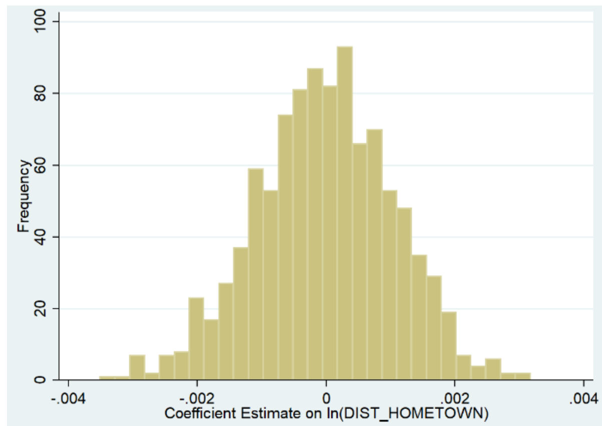
Figure 1: Placebo Tests

Figure 1 displays the distributions of the coefficient estimates on ln(DIST_HOMETOWN) from placebo regressions using specifications from Panel A of Table 2. The placebo process reshuffles CEO's birth counties 1000 times but maintains the original data structure by drawing CEO's birth counties from the original distributions without replacement. The dependent variables are ln(MORTGAGE_LOANS) (Panel A), MORTGAGE_GROWTH (Panel B), APPROVAL_RATE (Panel C), and ln(BRANCHES) (Panel D).

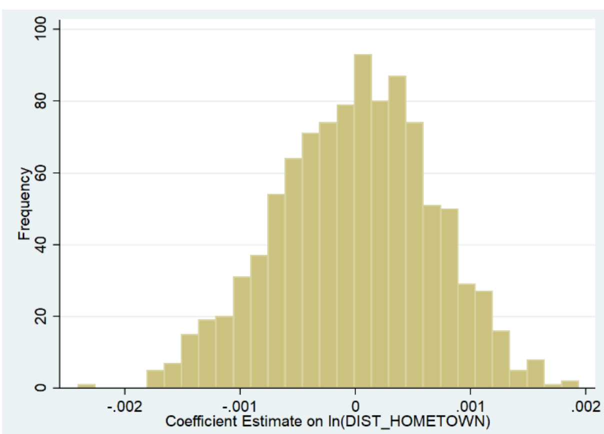
Panel A: LN(MORTGAGE_LOANS)



Panel B: MORTGAGE_GROWTH



Panel C: APPROVAL_RATE



Panel D: ln(BRANCHES)