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By *Ivan Lim, Duc Duy Nguyen, Linh Nguyen, John O.S. Wilson*

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## Abstract

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**JEL Classification:** E51, G21, G41
**Keywords:** Mortgage lending, Proximity, Banking, Branches, Geographic expansion

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## 1. Introduction

Over the past few decades, US banks have become more geographically dispersed. This is in part due to the consolidation of the banking industry in response to deregulation and technological change (Berger and DeYoung 2006). Consequently, bank branches that provide financial intermediation services to local constituents are now located farther from their bank's headquarters. As shown in Figure 1, the average distance between a bank's headquarters and its constituent branches has increased from approximately 80 miles in 1994 to 350 miles in 2021. In this paper, we examine whether, and how, the proximity between a bank's headquarters and its branches affects branches' operational efficiency.

**[Figure 1 around here]**

We proxy headquarters-to-branch proximity using travel time. Specifically, we follow Giroud (2013) and exploit the introduction of passenger airline routes to identify reductions in travel time between headquarters and local branches. Given that headquarters' managers are time-constrained, we expect that reductions in travel time increase the likelihood of visits by headquarters' managers to local branches. Consequently, reduced travel time from bank headquarters exposes a branch's operations to increased monitoring (Bernstein, Giroud, and Townsend 2016, Giroud 2013).

On the one hand, greater headquarters-to-branch distance may impede branch operational efficiency by exacerbating distance-related agency conflicts and hindering the ability of headquarters' managers to monitor branch staff (Berger and DeYoung 2001, Brickley, Linck, and Smith 2003). Given that distant branches are subject to less scrutiny from headquarters, employees of these branches could become inefficient and exert minimum work effort to "enjoy the quiet life" (Aghion and Tirole 1997, Bertrand and Mullainathan 2003, Kalnins and Lafontaine 2013). For instance, branch employees may fail to encourage customers to take up loans, or respond slowly to the needs of current and potential customers (Agarwal and Ben-David 2018). Consequently, following the introduction of new airline routes that increase the likelihood of visits and monitoring by headquarters' managers, branch managers and employees might respond by providing better service quality and working harder and more efficiently across different business lines and back-office functions, resulting in increased outputs (Dou and Roh 2023, Houston, Shan, and Shan 2021).

On the other hand, headquarters-to-branch distance could shield the branch from the bad practices and inefficiencies imposed by headquarters' senior managers unfamiliar with local communities (Berger and DeYoung 2001). Therefore, more frequent visits and monitoring by headquarters' managers could result in lower branch productivity and morale, leading to lower outputs.

We measure branch outputs and efficiency using mortgage lending for several reasons. First, this approach enables the use of granular loan-level mortgage data for almost the full universe of mortgages originated by US banks. Second, it allows us to observe the eventual performance of these loans. This has the advantage of directly measuring branch efficiency and outputs; in contrast, other branch-level products such as deposits or small business loans may not have equivalent performance measures. Finally, given the size and significance of the US residential mortgage market (which accounts for approximately 70% of all outstanding credit to households), it is important to understand mechanisms driving mortgage market outcomes (Kothari, Blass, Cohen, and Rajpal 2020).

Using a standard difference-in-differences framework, we examine how mortgage lending is affected by reductions in travel time between bank headquarters and local branches following the introduction of passenger airline routes. Treatment is defined at the headquarters-branch-county pairs level. Specifically, a headquarters-branch county pair is treated if the introduction of a new airline route has reduced the one-way travel time between the bank's headquarters and branches in that county by at least one hour. In total, 1,416 unique pairs of headquarters-branch counties are treated, with an average one-way travel reduction of 1.5 hours. This represents a substantial reduction, given that the average one-way travel time between a headquarters-branch county pair in our sample is 2.8 hours.[1]

All regressions include county-year and bank-county fixed effects. The inclusion of county-year fixed effects means that we are comparing treated branches to a group of unaffected control branches located in the same county in the same year. Therefore, the inclusion of county-year fixed effects controls for time-varying local shocks that could be correlated with both the introduction of new flight routes and local economic conditions as well as local lending. The inclusion of bank-county fixed effects partials out any time-invariant characteristics across the counties in which each bank has branches, thereby accounting for persistent preferences that a bank might have in lending to specific regions.

We find that the introduction of a new airline route that significantly reduces the travel time between a bank's headquarters and a given branch leads to a 5.5% increase in mortgage lending relative to control branches. Moreover, within the same bank, the proportion of mortgage lending at treated branches increases by 0.9% compared to other branches, suggesting that our results are not driven by overall increases in bank lending. Our findings are also robust to the inclusion of additional underwriting variables that capture loan credit risk and underwriting technologies. Overall, our evidence is consistent with the view that headquarters-to-branch

[1] In Section 4.3, we show that the magnitude of the treatment effect varies in proportion to the reduction in travel time.

distance induces distance-related agency conflicts and that reducing headquarters-to-branch travel time allows headquarters managers to monitor local branches more intensively. As a result, branches become more efficient and lending increases.

One caveat of our study is that we only observe reductions in travel time, and not actual headquarters' monitoring visits to branches. With this in mind, we conduct additional tests that exploit heterogeneity in time constraints and local monitoring incentives to provide additional circumstantial evidence supporting this conjecture. Since headquarters' managers are time constrained, they are more likely to visit and monitor local branches when flight introductions produce significant time savings. Indeed, we show that the magnitude of the treatment effect varies in proportion to the amount of time saved. Moreover, we also find that the treatment effect is stronger in counties where lending by local branches makes up a larger proportion of the bank's total lending activities. This supports the conjecture that headquarters' managers are more likely to exploit reductions in travel time to monitor branches that are more important to the bank, and is consistent with the idea that reductions in travel time facilitate local monitoring.

We perform several additional tests to ascertain the validity of our empirical design and to provide further evidence that our baseline results are unlikely to be driven by omitted variables such as local economic shocks that drive both local lending and the introduction of flights. First, we decompose *Treatment* into a set of indicators for years around the treatment, and find no statistically significant effect in the years leading up to the treatment. This suggests that lending is similar for both treated and control branches before treatment, validating the parallel trend assumptions and alleviating concerns of reverse causality.[2]

[2] If this were the case, we should observe increases in lending to take place before the treatment, not after.

Second, we find that the introduction of cargo flights that significantly reduce the travel time from headquarters does not affect the outputs of treated branches. The insignificant treatment effect for cargo routes indicates that changes in local economic conditions are unlikely to drive our results, given that both passenger and cargo routes could be initiated as a result of booming economic conditions in a given location. Third, we show that our results are robust to considering only new flight routes that are introduced as a result of a merger between two airlines. Arguably, the decision of two airlines to merge is unlikely to be driven by local conditions in a single location or a headquarters-branch pair specific shock. Overall, while we are unable to unambiguously rule out alternate interpretations, our evidence is consistent with the conjecture that headquarters make use of reductions in headquarters-to-branch travel time to more monitor branches closely.

Next, we conduct several cross-sectional tests to further understand how reductions in headquarters-to-branch travel time can mitigate distance-related agency problems. First, we show that after treatment, lending to minority borrowers increases, and particularly so to African American and Asian borrowers. One interpretation of this finding is that more stringent headquarters' monitoring motivates branch employees to work harder to support groups of borrowers that may require more consideration. Second, we show that the treatment effect is stronger in the earlier years of our sample period, suggesting that improvements in telecommunication technologies can partially alleviate distance-related agency problems. Finally, we detect statistically significant treatment effects in all bank size classes except the smallest banks with book assets below $1 billion. One implication of this finding is that because larger banks account for a disproportionately larger percentage of mortgage loans in the US, any potential efficiency gains as a result of reducing distance-related agency conflicts could have substantial impacts on home ownership, social welfare, and the real economy.

Having shown that a reduction in travel time between headquarters and local branches leads to an increase in lending, we next examine its effect on loan performance. On the one hand, flight introductions could facilitate more frequent headquarters' visits and stringent monitoring. This could motivate branch employees to work harder to carefully screen loan applications, engage in careful record keeping, and closely conform to recommended procedures, thus resulting in lower loan delinquencies (Heese and Pérez-Cavazos 2020). On the other hand, more frequent visits from headquarters could lead to an increase in loan delinquencies if too much pressure is exerted on branch employees to increase outputs (Tzioumis and Gee 2013). An increase in loan delinquencies following flight introductions would also be consistent with headquarters' managers imparting bad practices and inefficiencies on branch employees.

Using a similar empirical specification with a full set of fixed effects, we find that loans originated in treated branches are 1.7% less likely to become delinquent than loans originated in control branches. Importantly, these estimates control for applicants' FICO scores and loan-to-value ratios, and can therefore be viewed as capturing incremental subjective attributes over and above the variation attributable to common borrower risk characteristics. This is in line with the explanation that more intense monitoring by headquarters leads to more efficient branches.

In the final set of tests, we consider two non-mutually exclusive channels through which reductions in headquarters-to-branch travel time leads to increases in lending volume and loan performance: (1) loan prospecting and (2) loan screening. The first channel, *increased loan prospecting*, posits that branch employees work harder to seek new customers (Agarwal and Ben-David 2018). Consistent with this view, we observe an increase in the number of applications received by treated branches after treatment. Moreover, treated branches attract higher-income and lower risk applicants following treatment.

The second channel, *increased loan screening*, posits that treated branches' employees become more efficient in the loan screening process. When branch employees proactively communicate with riskier customers about the likelihood of their loans being approved, customers will not have to go through a lengthy loan application process that is likely to result in rejection. Moreover, branch employees will also have the opportunity to guide customers into resubmitting a more eligible application in the future. Consistent with this channel, we find that treated branches are 11.5% more likely to recommend the withdrawal of low-quality applications, such as those with high loan-to-income ratios.

## 2. Literature Review and Contributions

Our study is related to three strands of literature. First, it is related to studies on bank organization and control. Several studies focus on whether senior managers at lead banks within multibank holding companies (MBHCs) can effectively exert control their affiliate banks. Berger and DeYoung (2001) document that parent banks are able to exercise control over the efficacy of their bank affiliates. This control dissipates with distance from their affiliates, indicating distance-related agency conflicts, although these effects appear relatively modest. Berger and DeYoung (2006) show that MBHCs' control over their affiliates has been increasing over time, and that agency costs of distance have been decreasing.

Senior management can also exercise control over individual branches of the bank. Earlier studies that examine a single bank's organizational form find that banks exercise low levels of control over the performance of its branches (Berger, Leusner, and Mingo 1997, Schaffnit, Rosen, and Paradi 1997). In contrast, Brickley, Linck, and Smith (2003) study Texas banks and find that rural banking offices are more likely than urban offices to be locally owned. The authors explain that rural offices are afforded decision-making autonomy at the local-level due to the prevalence of distance-related agency conflicts that impede the monitoring and control of distant rural offices. Relatedly, Bos and Kolari (2005) find that bank efficiency declines with increased dispersion of branches, supporting the view that a greater distance between headquarters and branches increases agency conflicts within banks.

Second, our paper is related to the literature on the benefits and costs of banks' geographic expansion, namely the trade-off between the benefits of economics of scale and scope and the costs of inferior organizational design and exacerbation of agency costs. Evidence on whether geographic expansion provides benefits to banks is somewhat mixed and depends on the sample and time period investigated and the methodology used. Some studies show that geographic expansion is beneficial to overall bank outcomes. For instance, Deng and Elyasiani (2008) and Hughes, Lang, Mester, and Moon (1999) find that geographic expansion can result in higher bank valuation and better performance due to scale and scope efficiencies as well as better investment opportunities. Levine, Lin, and Xie (2021) offer further support for this by showing that geographic diversification lowers bank funding costs. Geographic expansion can also reduce bank volatility by lowering exposure to idiosyncratic local shocks (Goetz, Laeven, and Levine 2016) and can lead to better risk-return frontiers (Hughes, Lang, Mester, and Moon 1996).

One channel through which geographic expansion leads to higher valuation and lower risk is through the insulation of distant branches from headquarters' senior managers, who themselves are a source of problems. Specifically, increases in distance to the headquarters due to geographic expansion serve as a barrier to prevent headquarters' managers from imparting bad practices or interfering with the operations of the branches. For instance, headquarters' managers who are not familiar with the local communities may insist on marketing strategies or loan screening procedures that are ill-suited to the region in which local branches operate.

Other studies point to the negative effects of geographic expansion on bank outcomes. Geographic expansion can exacerbate agency issues by creating larger and more complex banks that give insiders (e.g., managers) greater flexibility and power to extract private benefits (Baele, Jonghe, and Vennet 2007). Moreover, geographic expansion can lead to value losses when managers enter new markets without relevant skills or local knowledge, or when expansion is driven by empire building motives (Acharya, Hasan, and Saunders 2006, Denis, Denis, and Yost 2002). Further, holding managerial skills constant, expansion could also harm bank performance because it is more challenging to manage a larger and more dispersed bank (Berger and DeYoung 2001). Consistent with this view, Laeven and Levine (2007) find that there is a diversification discount for financial conglomerates that engage in multiple activities as compared to specialized financial institutions. Goetz, Laeven, and Levine (2013) more directly show that geographic diversification reduces bank valuation, increases insider lending, and reduces loan quality. They conclude that the intensification of agency problems outweighs any benefits achieved from diversification. Furthermore, the benefits of diversification do not necessarily translate into lower risk because diversified banks might engage in riskier activities (Demsetz and Strahan 1997).

Geographic expansion could also exacerbate distance-related agency conflicts. It is challenging for senior headquarters' managers to remotely monitor branch employees' effort and service quality, and to understand local economic conditions (Berger and DeYoung 2001, Brickley, Linck, and Smith 2003). Given that distant branches are subject to less intense headquarters' monitoring, branch managers and employees could become inefficient and exert less effort in order to "enjoy the quiet life" (Aghion and Tirole 1997, Bertrand and Mullainathan 2003, Kalnins and Lafontaine 2013). Moreover, differences in (working) culture, norms, and values as a result of headquarters' managers and branch employees being in distant locales could also exacerbate these agency conflicts and lead to more red tape and organizational bureaucracy, resulting in branch inefficiency (Lim and Nguyen 2021). In support of this view, Deng and Elyasiani (2008) find that increased distance between a bank's headquarters and its branches reduces bank value and increases bank risk.

Third, our study is also related to the literature on the effects of technological progress in banking.[3] Technological progress has led to increases in bank productivity as banks take advantage of improvements in information processing, telecommunications, and financial technologies (Berger 2003). For example, He, Jiang, Xu, and Yin (2022) show that investments in different categories of information technology have varied impacts on the efficiency of different lending types. The adoption of, and advances in small business lending technologies have enabled banks to lend to increasingly distant small businesses (Brevoort and Hannan 2006, Hannan 2003, Petersen and Rajan 2002). These findings are consistent with the hypothesis that technological progress has increased banks' ability to control their affiliates and reduce the agency costs of distance (Berger and DeYoung 2006). DeYoung, Glennon, and Nigro (2008) show further evidence of this by explaining that the adverse effects of distance in small business lending can be dampened by the use of hard lending technologies.

Our paper contributes to these three strands of literature. First, our central findings affirm the existence of distance-related agency conflicts within the same bank and their effects on branch outputs and efficiency, thereby contributing to the understanding of the costs and benefits of banks' geographic expansion. Furthermore, we exploit a quasi-natural experiment that reduces travel time

[3] See Berger and Black (2019) and Liberti and Petersen (2019) for reviews on lending technologies and their relationship with hard and soft information.

between banks' headquarters and their branches. This approach also allows us to exploit within-bank variation and hold constant a bank's organizational form and its comparative advantage in lending technologies (Berger et al. 2005). While we acknowledge that we are unable to directly observe headquarters' monitoring visits, this approach allows us to more precisely identify a way in which agency issues within a bank manifest, and correspondingly, in headquarters' managers ability to centrally monitor distant branches to mitigate these issues.

One key takeaway of our findings is that despite rapid progress in technology in recent decades, in-person headquarters' monitoring of branches is still relevant, although its effects are decreasing over time. This suggests that in-person monitoring and communication are not perfectly substitutable by technology. This is consistent with findings investigating the evolution of small business lending, which has established that communication between bank employees is crucial due to organizational hierarchies and frictions in the production, transmission, and communication of soft information (Liberti 2018, Liberti and Mian 2008, Qian, Strahan, and Yang 2015, Stein 2002). By studying a hard information product like mortgage loans that does not necessitate itself to the use of soft information, we show that in-person monitoring can still have a first-order effect on lending outcomes, primarily through an "operational efficiency channel" as opposed to a "soft information communication channel."

In a related study, Levine, Lin, Peng, and Xie (2020) study how communications between bank headquarters' and branches affect aggregate small-business lending. A particularly novel and significant aspect of our paper is that we are able to link reductions in headquarters-to-branch travel time to the ex-post performance of individual mortgage loans. This allows us to show for the first time that increased internal monitoring within banks leads to superior local lending outcomes. This finding constitutes an important contribution of our work, given the limited empirical evidence regarding the impact of internal monitoring within banks on local lending performance. Further, exploiting the granularity of the mortgage data, we are able to document the direct economic channels through which increases in headquarters' monitoring affect local lending. More intensely monitored branch employees work harder to seek new customers, screen applications, and offer better service quality to increase branch efficiency.

## 3. Data and Variables

### 3.1. Headquarters' Managers and Onsite Branch Visits

Given that we cannot directly observe headquarters' visits to and monitoring of local branches, we rely on information from bank disclosures and regulatory examination guidelines to shed light on the importance of headquarters' onsite branch visits for the monitoring of branches and branch efficiency.

First, although mortgage lending decisions tend to be approved centrally at regional hubs or main headquarters and not at the branch, we argue that more intense branch monitoring could lead to increases in branch efficiency and outputs (in terms of loans originated). For instance, branch-level employees are likely to be the "face of the bank" and function as customer service agents that reach out to (potential) mortgage applicants (Houston Shan, and Shan 2021). Branch employees are therefore in a position to prospect for new business and provide valuable services such as initial screening, communicating the mortgage application process, and answering any queries that potential customers might have (Agarwal and Ben-David 2018). Accordingly, better service quality at the branch-level can result in a larger number of mortgage applications being submitted for approval (Dou and Roh 2023, Hayes, Jiang, and Pan 2021). All else being equal, this translates into a larger number of loans being approved and originated.

For instance, according to the job description of home mortgage loan officers at Wells Fargo (one of the biggest mortgage lenders in the US), the core responsibilities of loan officers include generating mortgage business, completing loan applications, building relationships and communicating with clients, and providing advice and guidance to clients.[4] This suggests that branch employees play an important role in the mortgage origination process, including seeking, screening, and interacting with clients. Therefore, it is natural to expect headquarters' managers to regularly visit branches to better understand local business conditions and to monitor branch employees.

Second, the importance of headquarters' onsite branch visits is evidenced by the fact that banks have various personnel whose main responsibility is to conduct onsite branch monitoring. These roles include compliance managers, internal auditors, and even more senior positions such as vice presidents. For example, at JPMorgan, one of the key roles of a compliance manager is to conduct onsite visits to review branch sale practices, monitor branches, and evaluate compliance risk.[5] Similarly, even at smaller banks such as Republic Bank, compliance managers are also required to travel between different facilities to oversee business units and prepare internal monitoring reports.[6] These examples indicate that managers from headquarters regularly visit local branches to evaluate branch performance.

Third, regulators also emphasize the importance of banks' headquarters conducting onsite branch visits. For example, the Federal Reserve Board, in its Commercial Bank Examination Manual (2020, p. 19), states that commercial banks' work program for internal control procedures

[4] See https://www.indeed.com/viewjob?jk=7b40eafbe8be95c6&from=serp&vjs=3
[5] See https://www.linkedin.com/jobs/view/ccor-compliance-manager-vice-president-at-jpmorgan-chase-co-2006375293/?fbclid=IwAR3LKBxhqlDJqeNvJyUhfu4JpbQb3dGyGvMtbBimgI0q6A1COjUhF6c8g8g
[6] See https://www.linkedin.com/jobs/view/3311005688/?refId=wyocwAGfM%2FvFlErIGW8rbA%3D%3D

should include physical inspection to verify selected transactions.[7] Likewise, the Office of the Comptroller of the Currency, in the Comptroller's Handbook (2016, p. 28), recommends that banks verify transactions through physical inspection visits. Banks are also required to authorize internal auditors to access and communicate with any member of staff at local branches (p. 18).[8] This suggests that in-person communication and information acquisition for monitoring takes place across different locations and managerial levels within banks.

### 3.2. Calculating Travel Time

To determine the travel time for each headquarters-branch pair in each year, we follow Ellis, Madureira, and Underwood (2020) and make the following assumptions. We first assume that driving is the optimal means of transportation when the travel distance between two locations is below 100 miles. We calculate drive time using Microsoft MapPoint North America. In our sample, 57.7% of headquarters-branch pairs are less than 100 miles apart. The average one-way drive time for these pairs is 50 minutes.

For locations that are more than 100 miles apart, we compare the drive time with the shortest flight time and designate the smaller of the two as the optimal travel time. To determine flight times between banks' headquarters and branches, we obtain data on US domestic airline routes from the T-100 Domestic Segment Database maintained by the Bureau of Transportation Statistics (BTS) – a branch within the US Department of Transportation. The T-100 dataset begins in 1990 and tracks all domestic US flights on a monthly basis. The data include, for example, flight origin and destination airports, total ramp-to-ramp flight duration, total number of flights, and

[7] See https://www.federalreserve.gov/publications/files/cbem.pdf
[8] See https://www.occ.gov/publications-and-resources/publications/comptrollers-handbook/files/internal-external-audits/pub-ch-audits.pdf

aircraft types. We exclude non-passenger flights (e.g., cargo only flights) and only retain flights listed as Class “F” (scheduled passenger services).

We use the A* search algorithm to calculate the shortest flight time for each headquarters-branch pair in each year. We consider door-to-door flight time, measured as the sum of: (1) the drive time from the bank’s headquarters to the departure airport (we identify locations of airports by matching the T-100 Domestic Segment Database with the Master Coordinate Table from BTS); (2) the waiting time at the airports (we allow 60 minutes waiting time in each departure and arrival airport); (3) the actual duration of the flight(s) (we determine the flight duration between a pair of airports with direct flights using the annual average across all flights between these two airports); and (4) the drive time from the arrival airport to the branch. In our sample, 42.3% of headquarters-branch pairs are more than 100 miles apart and the average optimal travel for these pairs is 5 hours and 30 minutes. Using this approach, we are able to construct a panel dataset of the optimal travel time for each bank headquarters-branch pair.

### 3.3. Defining Treatment

Having constructed a panel dataset on the optimal travel time between each bank headquarters-branch pair in each year, we proceed to describe how we identify our treatment group. We define treatment at the level of headquarters-branch county pairs.[9] A headquarters-branch county pair is considered as treated in year *t* and later if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank’s headquarters county and any of its branches in a given county by at least one hour. To illustrate, consider Compass Bank, which has four branches in Boulder County, Colorado. In March 2004, a new flight was introduced by

[9] Although the flight data are available on a monthly basis, we define treatment at the annual level because HMDA data are only reported annually.

SkyWest Airlines between Birmingham-Shuttlesworth International Airport and Denver International Airport that reduced the travel time from Compass Bank's headquarters in Jefferson County, Alabama to each of the four branches in Boulder County, Colorado by 55, 65, 70, and 75 minutes, respectively. Because there is at least one branch of Compass Bank in Boulder County that experiences at least a 60-minute reduction in travel time to headquarters, we consider all branches in that county as treated during and after 2004.

We define treatment at the county-level instead of at the individual branch-level because we are unable to observe the exact branch that handles each mortgage application.[10] We believe this is not likely to affect our results. First, it is very unlikely that headquarters' managers only visit a single bank branch in a local visit. Instead, because branches of the same bank in the same county are geographically proximate (the average distance between them is 9.3 miles), headquarters' managers are likely to utilize the same trip to visit multiple branches in the region. Second, potential noise is likely to be distributed evenly across the sample, and should broadly cancel out on average. Finally, as shown in Section 4.4, we obtain robust results when restricting the sample to treated counties where treated banks have only one branch. In these cases, our treatment is effectively at the branch level.

In total, there are 1,416 unique pairs of headquarters-branch counties that were treated, reducing the travel time between headquarters' counties and branches' counties by at least one hour. The vast majority of the treated county pairs (1,400 out of 1,416) are considered treated due to the introduction of new flight routes. Of these 1,400 treated pairs, 1,065 pairs are treated because a new direct flight was introduced to connect the two counties. Further, 335 pairs are treated due to the introduction of a new flight that led to a reduction in the number of transits, for instance

[10] Instead, we rely on the property's county to infer the location at which the loan is originated.

from two connections to one connection. Finally, 16 county pairs is designated as treated due to the introduction of a new highway that made driving faster than flying.[11]

**[Figure 2 around here]**

However, a concern is that the introduction of new flight routes is not entirely random. For instance, new routes could be introduced as a response to changing regional economic conditions that also affect mortgage lending. Figure 2 displays the geographic distribution of treated bank headquarters-branch county pairs during the sample period from 1994 to 2021. The locations of these treated pairs appear to be distributed evenly across the US. Nevertheless, in order to account for the possibility that the introduction of new routes could be driven by changing local economic conditions, all regression specifications include county-year and bank-county fixed effects. We discuss this in detail in Section 3.5.

### 3.4. Sample Construction

To construct our sample, we begin by obtaining a list of all commercial US banks with available financial data from Call Report (FR Y-9C forms) filings. Next, we merge this bank-level dataset to the Home Mortgage Disclosure Act (HMDA) database collected by the Federal Financial Institutions Examination Council. The HMDA database is a loan-level dataset that covers all mortgage applications that have been assessed by qualified financial institutions. Specifically, an institution is required to disclose any mortgage lending under the HMDA if it has at least one branch office in any metropolitan statistical area, and meets the minimum asset size threshold. For instance, in 2007, the median year in our sample, this reporting threshold was $36 million in book

[11] Given that the vast majority of new travel routes in our sample are new flight routes, we refer to these routes as new flight routes.

assets.[12] Given the relatively low asset size reporting threshold, this dataset covers the majority of lenders and accounts for approximately 90% of US mortgage originations (Cortés, Duchin, and Sosyura 2016).

Each loan application in the dataset contains information on borrower demographics (e.g., gender, race, and income), loan characteristics (e.g., requested loan amount and its purpose and type), the decision on the application (e.g., approved, denied, or withdrawn), the location of the property, the year in which the loan application decision is made, and the lender's identity. We merge this loan-level dataset with a list of branches of US banks from the Federal Deposit Insurance Corporation's (FDIC) Summary of Deposits (SOD) database. Because the SOD's coverage commences in 1994, our sample period is 1994–2021.

Given the substantial computing power required to estimate the large number of fixed effects included in our empirical model, following Dell'Ariccia, Igan, and Laeven (2012), we construct a stratified sample using 10% of the individual loans from the HMDA dataset on a bank-county-year basis and estimate the model using the stratified dataset. Given the large size of our dataset and the law of large numbers, this sampling choice should not affect our results.[13]

We then follow the screening procedure of Cortés, Duchin, and Sosyura (2016) to minimize data errors. First, we exclude applications that were closed for incompleteness or withdrawn by the applicant before a decision was made. Second, using the annual FDIC's SOD dataset on locations of bank branches, we exclude loan applications filed with banks that do not have a physical branch in the county of the mortgage property. These observations are likely to contain

[12] The HMDA's reporting criteria can be found at https://www.ffiec.gov/hmda/reporterhistory.htm.
[13] In unreported analyses, we find that our results remain unaltered when we use five different stratified samples. These results are available upon request.

loan applications that the borrower completed online or through a third-party mortgage company without any contact with branch employees.

### 3.5. Model and Specification

The main premise of our empirical design is that because headquarters' managers are time-constrained, a reduction in travel time between headquarters and local branches will increase the likelihood and frequency of these managers visiting local branches. The increase does not need to be large; for instance, an increase in visit frequency from once to twice a year could allow headquarters to have a much better understanding of local socio-economic conditions and monitor branch employees more effectively. To examine the treatment effects on local lending and performance, we use a difference-in-differences approach and estimate the following model:

$$y_{ijkt} = \alpha_{ijkt} + \beta_1 * Treatment_{ikt} + \beta_2 * \boldsymbol{L}_{ijkt} + \beta_3 * \boldsymbol{X}_{it} + \gamma_{kt} + \sigma_{ik} + \varepsilon_{ikt}, \tag{1}$$

where $i$ indexes bank, $j$ indexes loan, $k$ indexes branch county location, and $t$ indexes year. $y_{ijkt}$ is the dependent variable of interest. In most specifications, $y_{ijkt}$ is a dummy variable that equals one if a loan was approved and zero otherwise (*Approved*). In our loan performance analysis, $y_{ijkt}$ is a dummy that equals one if a loan becomes delinquent, and zero otherwise (*Delinquent*). Our main variable of interest $Treatment_{ikt}$ is a dummy that equals one if at some point in or before year $t$, a new flight route is introduced that reduces the travel time between the bank's headquarters county and branches in county $k$ by at least one hour. Our control group includes all branches that have not been (or are yet to be) treated. Because of the staggered introduction of new airline routes, a branch remains in the control group until it is treated (which, for some branches, is never). $\boldsymbol{L}_{ijkt}$ and

$\boldsymbol{X}_{it}$ are vectors of loan and bank control variables, respectively, and $\gamma_{kt}$ and $\sigma_{ik}$ represent county-year and bank-county fixed effects, respectively.

Admittedly, an airline's decision to introduce a new flight route is not random and depends on several factors including economic conditions and the business and strategic considerations of a given airline (Giroud 2013). If there are omitted variables that are driving both the introduction of new flight routes and branch-level output and efficiency, then our results will be biased. To illustrate, suppose local economic conditions in Boulder County are booming. Big corporations could be more likely to locate or expand to Boulder County, which increases the local labor force and simultaneously, the demand for mortgages. At the same time, airlines may find it more attractive to introduce new flights connecting Boulder County to other parts of the country. If so, our empirical strategy would yield spurious results.

We discuss how the inclusion of county-year and bank-county fixed effects alleviate this concern in our model. By adding county fixed effects interacted with year fixed effects, we are comparing treated branches to a group of unaffected control branches located in the same county in the same year (e.g., Boulder County in year 2004). This is possible because branches in Boulder County can belong to banks headquartered in different locations, only some of which have newly introduced airline routes connected to Boulder County. The inclusion of county-year fixed effects thus controls for all time-varying branch-level shocks at the county-level, such as economic conditions, local business cycles, industry consumption, and housing demand (Gilje, Loutskina, and Strahan 2016). Although we acknowledge that the introduction of airline routes is not random, the inclusion of county-year fixed effects alleviates some concerns related to local demand driving our results.

The inclusion of county-year fixed effects, however, does not account for the persistent preferences that a bank might have in lending to specific regions. For instance, suppose there is a shock that makes branches in some specific regions more attractive for a certain bank, so that the bank increases lending in these regions after the shock while other banks do not. This shock may also drive the introduction of new routes that connect the bank's headquarters and these branches because this bank might lobby for more direct flight routes. By adding bank fixed effects interacted with county fixed effects, we partial out any time-invariant characteristics across the counties in which each bank has branches. This allows us to focus on within-bank-county variations in mortgage lending following the introduction of new routes.

Under this specification, the estimated coefficient on *Treatment* is a difference-in-differences coefficient that compares changes in lending and performance between two sets of otherwise similar branches in the same county. One set of branches experiences the introduction of new routes, which significantly reduces the travel time between the bank's headquarters and the branch's counties, while the other set of branches does not. The first difference is between branches in a county that are treated with the introduction of new routes and branches in the same county that are not treated. The second difference is the comparison of lending by branches in the county before and after treatment.

Our vector of loan controls ($\boldsymbol{L}_{ijkt}$) includes *Ln(Applicant income)* and *Loan-to-income* ratio. Dummy variables are also included to capture: whether the applicant is *Female, African American*, *Asian,* or *Other Non-White;* whether the loan purpose is for house improvement (*Improve*) or for refinancing (*Refinance*); and whether the loan type is Federal Housing Administration (*FHA*)-insured, Veterans Administration (*VA*)-guaranteed, or Farm Service Agency or Rural Housing Service (*FSA/RHS*). Additionally, because branches have capacity limits and the internal capital market of banks have frictions (e.g., Houston, James, and Marcus 1997), we further control for the total number of mortgage loan applications received at the bank-county-year level *Ln(# applications bank-county-year)* and at the bank-year level *Ln(# applications bank-year)*. Bank controls $\boldsymbol{X}_{it}$ include *Ln(Assets)*, *ROA*, *Deposits/Assets*, and *Loan/Assets*. To further control for the size distribution of banks, we include two size class dummies: *Midsize Bank* (total assets > \$1 billion and total assets ≤ \$60 billion) and *Large Bank* (total assets > \$60 billion).[14] The size category that is omitted due to perfect multicollinearity is community banks with less than \$1 billion in assets. Appendix 1 presents detailed definitions of the variables used in the empirical analysis.

**[Table 1 around here]**

Table 1 shows the summary statistics, which are in line with those reported in the prior literature (e.g., Cortés, Duchin, and Sosyura 2016). On average, 76% of mortgage applications were approved. The average applicant earns about \$108,100 per year and requests a mortgage loan of \$167,700. The average loan-to-income ratio is 1.92.

## 4. Results

### 4.1. Main Results: Mortgage Lending

Table 2 presents the loan-level regression results examining the impact on local mortgage lending following reductions in travel time between banks' headquarters and their constituent branches. The dependent variables are: *Approved*, a dummy variable that equals one if a loan is approved and zero otherwise (Column (1)); and *Ln(Loan amount)*, the natural logarithm of the nominal

[14] The \$60 billion size threshold for midsize banks follows the definition from Midsize and Community Banking Supervision:https://www.occ.treas.gov/about/who-we-are/organizations/midsize-and-community-bank-supervision/index-midsize-and-community-bank-supervision.html. Our results are robust to alternative size cut-offs, such as \$50 billion or \$100 billion. The results are available upon request.

dollar value of the loan (Column (2)). The regressions on mortgage approvals in Column (1) tell us whether treated branches are more likely to approve mortgage applications, while the regressions on loan amount in Column (2) show whether treated branches originate larger loans following the introduction of new airline routes.

Across both outcome variables, the estimated coefficients on *Treatment* are positive and statistically significant. The results indicate that treated branches are, on average, more likely to approve a mortgage application (Column (1)) and originate larger loan amounts (Column (2)) following the introduction of new flight routes that reduce the travel time between headquarters and local branches by at least one hour.

**[Table 2 around here]**

Analyzing mortgage approvals and loan amounts separately does not tell us about the magnitude of the treatment effect on total lending volume. Therefore, in Column (3), we repeat the mortgage approval regressions, but now weight each observation by its loan amount. This weighted approach, used in Fuster, Plosser, and Vickery (2021),[15] ascribes more (less) weight in the approval regressions to larger (smaller) loans. The weighted regressions thus capture the effect of the introduction of new airline routes on the total mortgage *lending volume* that treated branches originate. As shown in Column (3), the coefficient on *Treatment* is positive and statistically significant, indicating that the mortgage lending volume increases by 5.5% more (=0.042/0.76) in treated branches relative to control branches. Given that the weighted regressions presented in

[15] Fuster, Plosser, and Vickery (2021) use a similar weighted approach to examine the effect of changes in regulatory oversight on mortgage originations.

Column (3) allow us to interpret the *Treatment* coefficient as changes in total lending volume (our proxy for branch outputs and efficiency), they are our preferred specification.[16, 17]

In Column (4) of Table 2, we test for any pre-shock differential in trends in local mortgage lending by examining the dynamic timing effects of flight introductions. We replace *Treatment* with a series of dummy variables: *Pre2* (*Pre1*) is a dummy that equals one for observations two (one) years before receiving treatment; *Zero* is a dummy that equals one for observations that are treated in the current year; *Post1* is a dummy variable that equals one for observations one year after treatment; and *Post2plus* is a dummy that equals one for observations two or more years after treatment.

A necessary condition for the parallel trends assumption to be plausible is that treated and control branches do not show significant differences in lending dynamics in the years prior to the shock. Consistent with this, the results in Column (4) indicate that statistically significant treatment effects on mortgage approval rates take place after, and not before, the treatment year. Specifically, the estimated coefficients on *Pre2* and *Pre1* are both statistically insignificant and economically negligible. This suggests that mortgage approval rates are similar for both treated and control branches prior to the flight introductions. In contrast, we observe positive and statistically significant coefficients on *Zero*, *Post1*, and *Post2plus*, indicating that the treatment effect is only detectable on and after flight introductions. Overall, the dynamic timing results suggest that the

[16] We do not use loan amount as our main dependent variable because it tends to confound borrower preferences and credit terms offered by banks. For instance, even if treated branches are willing to offer larger loan amounts, credit markets will not clear on these amounts if borrowers only require smaller amounts. Moreover, larger originated loan amounts do not necessarily indicate that treated branches increase their total lending volume (e.g., if treated branches approve larger loans, but reduce their approval rates, total branch lending might not increase).

[17] For the remaining of the paper, all loan-level regressions are weighted by loan amount. However, the choice of weighting does not alter our results and we continue to obtain qualitatively similar findings when using unweighted regressions.

parallel trends assumption is likely to be valid and that reverse causality (i.e., that increases in local lending lead to the introduction of new travel routes) is unlikely.

Taken together, our findings suggest that flight introductions between banks' headquarters and their branches lead to an increase in local lending. This is consistent with the interpretation that improvements in travel accessibility can mitigate the adverse effects of distance-related agency conflicts and improve the overall efficiency and control of branches. In Section 6, we perform additional analyses to better understand the mechanisms underlying these findings.

### 4.2 Controlling for Underwriting Variables

In this subsection, we perform two analyses to address the concern that our results could be driven by spurious correlations from omitted underwriting variables that might affect approvals. Our first test exploits the fact that starting from 2018, the HMDA database has started recording additional variables, including loan-to-value and debt-to-income ratios as well as the underwriting technology that lenders use to determine whether the applicant is qualified for the loan.

Consequently, in Panel A of Table 3, our analyses are based on a subsample of 2018–2021 HMDA data to and control for additional covariates that could affect mortgage approval decisions. In Column (1), we replicate the baseline specifications in Column (3) of Table 2. Column (2) augments the regressions with the following additional control variables: *Loan-to-value* and *Debt-to-income* ratios; *Ln(Property Value)*; and dummy variables indicating whether the applicant's age is below 45, whether the credit scoring model used is *Equifax*, *Experian*, *FICO Risk Score*, or *Vantage*, and whether the automated underwriting system used is *Desktop Underwriter*, *Loan Prospector*, *TOTAL Scorecard*, or *GUS*. In Column (3), we include loan-to-value bins fixed effects and debt-to-income bins fixed effects to account for the potential non-linear relationship between underwriting variables and mortgage approvals.[18] Finally, in Column (4), we include the interacted fixed effects between loan-to-value ratio bins and debt-to-income bins to further control for any possible non-linearity or peculiarities in credit quality.

Consistent with our main results in Table 2, the results in Panel A of Table 3 show that the treatment effect remains positive and statistically significant when we control for additional underwriting variables. Further, the magnitude of the estimates remains stable as we progressively introduce more control variables and fixed effects into the model. This suggests that our results are robust to the choice of controls included and that *Treatment* is a significant and consistent predictor of branch outputs.

**[Table 3 around here]**

As a second test, we follow Bartlett, Morse, Stanton, and Wallace (2022) and add census-tract-level averages of three underwriting variables that capture loan quality: the reported applicant's FICO score, loan-to-value ratio, and debt-to-income ratio. These variables are constructed using data from Black Knight's McDash database for loans that have been originated.[19] Although this test does not allow us to control for loan-level credit risk variables as in Panel A, it has the advantage of using the full baseline sample from 1994 to 2021. Panel B of Table 3 displays the results. We find that the coefficient on *Treatment* remains positive and statistically significant, and is similar in magnitude to our baseline estimate. Overall, the results in Table 3 alleviate the concern that our findings are driven by unobserved underwriting variables.

[18] We use 10 loan-to-value bins and 10 debt-to-income bins.

[19] This dataset covers approximately two-thirds of the US mortgage market and contains information on applicants' risk characteristics. Although the McDash database also has loan origination and performance data, the data license does not allow us to identify the lender that originates each mortgage. Therefore, if we were to analyze loan-level McDash data, we could not control for bank*county fixed effects and other bank-level characteristics.

### 4.3. Travel Time, Onsite Visits, and Headquarters' Monitoring

As mentioned previously (in subsection 3.1), given that we do not observe monitoring visits, our results are merely consistent with the conjecture that reductions in headquarters-to-branch travel time lead to increased managerial monitoring, and thus, improved local branch operating efficiency. In this subsection, we attempt to produce additional circumstantial evidence consistent with this conjecture by conducting various tests that exploit heterogeneity in time constraints and local monitoring incentives.

If travel time affects the likelihood and frequency of headquarters' managers visits to local branches, and that managers have time constraints, we should observe a weaker treatment effect for smaller reductions in travel time. In Column (1) of Panel A, Table 4, we include *Small treatment* to capture travel time reductions of more than 30 minutes but less than one hour. We find that the coefficient on *Small treatment* is not statistically significant and is economically indistinguishable from zero. In contrast, we continue to observe a statistically significant and economically substantial treatment effect for travel time reductions of more than one hour. This suggests that the magnitude of the treatment effect depends on the amount of time saved in travelling between headquarters and local branches. If travel time reductions do not translate into onsite branch visits and instead capture other omitted variables, the treatment effect should not vary with the magnitude of travel time reductions.

**[Table 4 around here]**

Column (2) of Panel A focuses on the effects of discontinued flight routes that significantly increase the travel time between headquarters and local branches. If travel time is related to onsite visits, we should detect an opposite treatment effect (i.e., lower mortgage lending) when travel time increases. We include *Reverse treatment* to capture increases in travel time for headquarters-branch county pairs of more than one hour. We observe a negative and marginally significant coefficient on *Reverse treatment* in Column (2). Thus, branch efficiency decreases when it becomes more time consuming for headquarters' managers to visit local branches. Again, the results indicate that travel time affects headquarters' frequency of branch visits.

Next, if reductions in travel time enable headquarters to monitor local branches more effectively, we should expect headquarters' managers to exploit these reductions to monitor branches that are more important to the bank. That is, treatment effects should be stronger in counties where lending by local branches makes up a larger proportion of the bank's total lending activities. To test this assertion, we interact *Treatment* with (1) *Branch loan amount/Bank loan amount,* the total dollar amount of mortgage loans originated by treated branches divided by the total dollar amount of mortgage loans originated by the bank in that year, and (2) *Branch customers/Bank customers*, the total number of mortgage loans originated by treated branches divided by the total number of mortgage loans originated by the bank in that year. The results are presented in Panel B of Table 4.

The estimated coefficients on *Treatment***(Branch loan amount/Bank loan amount)* and *Treatment***Branch customers/Bank customers* are positive and statistically significant, suggesting that when treated branches account for a larger proportion of the bank's total mortgage lending, headquarters are indeed more likely to take advantage of the reduced travel time to visit and monitor these branches. Overall, the results in Table 4 provide circumstantial evidence supporting the conjecture that travel time reductions facilitate more frequent visits between headquarters and local branches, thereby improving headquarters' monitoring of local branches. While this is comforting, in the next section, we further address the concern that the flight introductions could be related to other factors such as local economic shocks that drive our results.

### 4.4. Other Robustness Tests

In this subsection, we present results of various robustness tests on the baseline findings in Table 2. One concern related to our empirical strategy is that the introduction of new flight routes is not random but is instead correlated with economic conditions. If this were true, it would also discredit our conjecture that flight time reductions increase headquarters' monitoring visits and monitoring. Although the inclusion of county-year fixed effects and headquarters-branch county pair fixed effects partially alleviates some concerns of spurious correlations, we perform two analyses to further mitigate this concern.

First, we perform a placebo test focusing on cargo routes. While both commercial passenger and cargo routes could be initiated as a result of booming economic conditions in a given location, headquarters' managers would not be able to take advantage of the time saving from new cargo routes to more regularly visit and monitor local branches. Consistent with this, in Panel A of Appendix 2, we find that the introduction of new cargo routes that reduce headquarters-branch travel time by more than one hour does not significantly affect local lending. If our results were to be driven by booming economic conditions in a location, we should continue to find travel reductions from cargo routes to affect local lending. This finding also provides additional evidence that managers make use of reductions in flight time to visit branches, as treated branches only show increases in efficiency when passenger flight time is reduced, but not cargo flight time.

Our second test uses a subset of flight route introductions that are less likely to be the result of correlations with local shocks. More specifically, we focus on new flight routes that are introduced because of a merger between two airlines. Arguably, the decision between two airlines to merge is unlikely to be driven by local conditions in a single location or related to a headquarters-branch pair specific shock. Following Giroud (2013), we obtain a list of airline mergers from airlines' annual reports and newspaper articles. We then supplement this with merger data from Thomson Securities Data Corporation Platinum database. Using the list of 23 airline mergers between 1994 and 2021, we identify 462 out of 1,416 treatments that arise following a merger between two airlines. As shown in Panel B of Appendix 2, our results remain robust when we restrict treatment to those that arise from an airline merger.

Panel C of Appendix 2 presents other robustness tests. In Column (1), we address the concern that there may be noise in the regressions because we define treatment at the county level instead of the branch level. We show that our results are robust when we restrict the sample to treated counties in which treated banks have only one branch. In these cases, our treatment is effectively at the branch level. In Column (2), we use a shorter post-treatment window that ends five years after treatment.[20] This accounts for the possibility that headquarters only take advantage of travel time reductions in the first few years after flight introductions. Finally, in Columns (3) and (4), we exclude the years 2007–2009 (subprime crisis) and 2000–2001 (dot-com bubble). We obtain robust results across all columns. Overall, this section provides us with additional evidence that our results are less likely to be driven by changes in economic conditions or other factors that might affect the interpretation of our findings.

### 4.5. Heterogeneity in Treatment Effects

In this subsection, we evaluate whether the treatment effect differs across applicant demographic groups, time periods, and banks. We start by examining how reductions in headquarters-branch travel time affect credit to groups of borrowers that have historically been excluded from credit markets.

[20] In unreported results, we also obtain similar results when we restrict our analysis window to six, eight, or 10 years after treatment.

To test this, we interact *Treatment* with four dummy variables indicating whether the applicant is (1) Female, (2) African American, (3) Asian, or (4) Other Non-white. The results are presented in Panel A of Table 5. We find that the coefficients on the interaction terms *Treatment**African American* and *Treatment**Asian* are positive and statistically significant. This indicates that after treatment, mortgage applications by African American and Asian borrowers are more likely to be approved at treated branches. The interaction terms between *Treatment* and the other indicators of marginal applicants are not statistically significant. Because minority borrowers have less detailed credit histories, evaluating their applications may require more effort (Cohen-Cole 2011, Ergungor 2010, Frame et al. 2022). Therefore, as branch employees receive more scrutiny following reductions in headquarters-branch travel time, they exert more effort and improve their service standards to better support harder-to-serve customers (Begley and Purnanandam 2021).[21] Accordingly, these findings have implications for policies that aim to address economic inequality.

**[Table 5 around here]**

Next, we perform two tests to explore heterogeneity in the treatment effect over time. Our first test focuses on how the treatment effect changes over the sample period. Our sample period is 1994 to 2021, a period where major changes in telecommunication technologies occurred, including the widespread adoption of the Internet and videoconferencing technologies (Berger and Black 2019, He, Jiang, Xu, and Yin 2022). We therefore expect the treatment effect to be stronger in the early years of our sample period when technologies that facilitate remote communication and monitoring are less readily available. To test this, Panel B of Table 5 interacts *Treatment* with

[21] In Internet Appendix IA1, we show additional evidence that the treatment effect is more salient among loans that require more inputs from branch-level employees. This indicates that the enhanced headquarters' monitoring effect arising from travel time reductions is especially important in facilitating lending to mortgages that require greater inputs from branch-level employees.

dummy variables for two time periods: 1994–2007 (14 years) and 2008–2021 (14 years). Consistent with prior evidence that technological progress allows for improvements in organizational control (e.g., Berger and DeYoung 2006), we find that the magnitude of the treatment effect is approximately 13% lower in the 2008–2021 period compared to the 1994–2007 period. Nonetheless, our findings of significant treatment effects in the latter time period imply that proximity between branches and their headquarters is still important despite rapid advances in technology.

Our second test compares the treatment effect during crisis periods versus normal times from 1994 to 2021. This includes one banking crisis (a crisis that originated in the banking sector) and three market crises (crises that originated in financial markets). Following Berger and Bouwman (2013), the banking crisis is the subprime lending crisis (2007–2009).[22] The market crises are: (1) the Russian debt crisis and Long-Term Capital Management bailout of 1998; (2) the bursting of the dot.com bubble and the September 11 terrorist attacks in the early 2000s (2000–2002); and (3) the recent Covid-19 pandemic (2020–2021). Normal times are the years outside these crisis periods.

As shown in Panel C of Table 5, the coefficients on the interacted treatment dummy are 0.067 for the market crisis period, 0.047 for the banking crisis period, and 0.032 during normal times. While all the interacted coefficients are statistically significant below the 1% level, our findings indicate that the marginal benefits of reductions in headquarters-branch travel time are more impactful during periods of economic turmoil when there is likely to be more volatility in customer demand for loans.

[22] We find similar results using 2008–2009 instead of 2007–2009 as banking crisis years.

Finally, Panel D of Table 5 examines how the treatment effect varies across bank size classes by interacting *Treatment* with three size-class dummies: *Small Bank* (total assets ≤ \$1 billion), *Midsize Bank* (total assets > \$1 billion and total assets ≤ \$60 billion), and *Large Bank* (total assets > \$60 billion). Unsurprisingly, we find that the interacted treatment effect for small banks is not statistically significant. This is consistent with small banks having limited geographical coverage, and therefore travel time reductions are less likely to matter for these banks. In contrast, the interacted treatment dummies are statistically significant and similar in magnitude for both midsize and large banks. An important implication of this finding is that because a large proportion of mortgage loans in the US are originated by larger banks (Stanton, Walden, and Wallace 2014), any potential efficiency gains at these larger banks as a result of reducing distance-related agency costs can have substantial impacts on homeownership, social welfare, and the real economy (Antoniades and Calomiris 2020).

4.6. Other Lending Measures

Next, we show that our results are robust to alternative measures of local mortgage lending. Table 6 reports bank-county-year regressions and shows that the increase in lending in treated branches represents an increase in the branches' proportion of the bank's total lending activities in that year. This analysis allows us to more directly observe how reductions in headquarters-to-branch travel time for certain branches of the same bank affect the composition of its branch-level lending portfolio. We estimate the treatment effect on two previously defined outcome variables: (1) *Branch loan amount/Bank loan amount*, and (2) *Branch customers/Bank customers*. All regressions include county-year and bank-county fixed effects and similar bank-level controls to Equation (1) while loan-level controls are collapsed at the bank-county-year level. Appendix 1 provides detailed variable definitions.

**[Table 6 around here]**

The results in Table 6 indicate that after the treatment, the proportion of mortgage dollars originated in treated branches increases by 0.9% (Column (1)) and the proportion of new loans originated in treated branches increases by 1% (Column (2)) relative to the total mortgage lending activities of the bank in that year. The results suggest that reductions in headquarters-to-branch travel time led to higher branch-level outputs, and that the detected effects are not simply driven by an overall increase in lending at the bank-level.

## 5. Mortgage Performance

Having shown that a reduction in travel time between headquarters and local branches leads to an increase in lending volume, we next examine the treatment effect on loan performance. On the one hand, more stringent monitoring brought about by more frequent headquarters' visits could motivate branch employees to work harder to screen applications, maintain more careful record-keeping, and closely conform to recommended procedures. These could lead to lower loan delinquencies as branches become more efficient (Berger and DeYoung 2001, Heese and Pérez-Cavazos 2020). On the other hand, more frequent visits from headquarters could cause a decline in loan performance and branch efficiency if such visits put too much pressure on branch employees to increase outputs (Tzioumis and Gee 2013) or instill branch favoritism from headquarters in a way that impedes monitoring (Duchin and Sosyura 2013, Landier, Nair, and Wulf 2009).

To examine the effect of travel time reductions between headquarters and local branches on loan performance, we exploit a dataset compiled by Fannie Mae (Fannie Mae Single-Family

Loan Performance Data) that tracks ex-post performance of individual loans.[23] This dataset covers approximately one quarter of the US mortgage market and provides loan-level monthly status updates, including information on loan delinquencies, applicants' credit risk characteristics, and interest rates. Our dependent variable is a dummy variable that equals one if a loan becomes 90 days delinquent during the first two years of the loan's life.[24] Because the Fannie Mae dataset includes only conventional loans, we do not control for indicators of different loan types. We further include two additional variables that control for borrower risk made available in the Fannie Mae dataset: the applicant's FICO score and their loan-to-value ratio.

**[Table 7 around here]**

The results, presented in Table 7, indicate that loans originated in treated branches have lower rates of default. In the tightest specification in Column (3), the estimated coefficient on *Treatment* indicates that loans originated in treated branches are 1.7% less likely to become delinquent than loans with similar characteristics approved by the same bank but located in control branches. Importantly, these estimates already account for the "hard" quantitative components of the riskiness of the loan (e.g., FICO scores and loan-to-value ratios). Thus, our results can be viewed as capturing incremental subjective attributes over and above the variation attributable to common borrower risk characteristics.

Overall, the results are consistent with the view that the introduction of new flight routes facilitates more frequent visits from headquarters to local branches, which allows headquarters to monitor local branches more effectively. Consequently, branches become more efficient as

[23] 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.

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

employees exert additional effort to screen applications and evaluate potential borrowers, maintain more careful record keeping, and more closely conform to recommended procedures.[25] This results in a better mortgage performance alongside an increase in mortgage volume.

## 6. Economic Channels

This section considers two non-mutually exclusive channels through which a reduction in travel time between headquarters and local branches may lead to an increase in lending volume and loan performance in treated branches: (1) loan prospecting and (2) loan screening.

### 6.1. Loan Prospecting

The loan prospecting channel posits that reductions in headquarters-to-branch travel time would allow headquarters' managers to monitor employees' efforts more closely (Kalnins and Lafontaine 2013). This could motivate branch employees to work harder to seek new customers ("loan prospecting"). For instance, they could convince potential mortgage applicants from other banks to apply for loans at their bank by raising awareness of the bank's products (Agarwal and Ben-David 2018).

We perform two tests to understand the effect of travel time reductions between headquarters and local branches on the quantity and characteristics of loan application flows. First, we perform bank-county-year-level regressions to investigate the treatment effect on the application flow quantity. If branch employees work harder to attract more customers, we should observe an increase in the number of loan applications and amounts applied for received by treated

[25] We again caution that we are unable to directly observe headquarters' monitoring visits. As such, the interpretation of these findings hinges on the conjecture that headquarters' managers exploit travel time reductions to make more frequent visits to branches.

branches. For each bank-county-year, we calculate the natural logarithm of the total number of mortgage applications submitted (*Ln(# applications bank-county-year)*) and the total loan amount requested (*Ln(Total requested loan amount bank-county-year)*). We regress these variables on our *Treatment* dummy and display the results in Panel A of Table 8.

As shown in Panel A, the estimated coefficients on *Treatment* are positive and statistically significant across both outcome variables, indicating that the total number of loan applications and the total requested loan amount increase after treatment. The findings therefore suggest that customer prospecting is one channel through which branch efficiency improves following flight introductions. [26]

**[Table 8 around here]**

Second, we examine whether there is a change in the characteristics of mortgage applications received by treated branches. We focus on two applicant characteristics, *Ln(Applicant income)* and *Loan-to-income* ratio, and regress them on our *Treatment* dummy. The regressions are at the loan-level and include the full set of control variables and as well as county-year and bank-county fixed effects.

Panel B of Table 8 displays the results. We find that the average income of mortgage applicants at treated branches increases by 2.2% following treatment (Column (1)). We also find the applicants' loan-to-income ratio (which measures applicants' risk) decreases after treatment (Column (2)). We interpret the results as being attributable to treated branch employees working harder to expand the applicant pool and reaching out to higher-income and safer applicants.

[26] An alternate interpretation to this finding is that our empirical setup has not adequately controlled for unobserved variation (i.e., a change in local macro-economic activity) that could be correlated with both loan volumes and flight introductions. The inclusion of the two-way interacted fixed effects between county and year should alleviate this concern to some extent because it allows us to compare treated branches to control branches that are located in the same county in the same year. Therefore, both treated and control branches should face similar changes in macro-economic activities at the county-level.

### 6.2. Loan Screening

The second channel, loan screening, posits that branch employees work harder in the loan screening process. For instance, if branch employees believe that an application is unlikely to be approved they could recommend its withdrawal. When branch employees proactively communicate with riskier customers about the likelihood of their loans being approved, customers will not have to go through a lengthy loan application process that will eventually be rejected. This allows the bank to maintain a positive relationship with these customers, so that branch employees can guide them to submit a more suitable application in the future, increasing branch outputs.

**[Table 9 around here]**

Table 9 reports two tests examining the effects of flight introductions on the likelihood of loan withdrawal and characteristics of withdrawn loan applications. In Column (1), we restrict our sample to only withdrawn or rejected loan applications. This allows us to test whether loan applications at treated branches are more likely than those at control branches to be withdrawn, rather than to be rejected after going through the formal mortgage review process. Consistent with branch employees undertaking a more active role in the initial screening process, we find an 11.5% increase in the likelihood of loan applications being withdrawn as opposed to being rejected after treatment.

In Columns (2)–(4), we examine the characteristics of withdrawn applications. Using a sample of withdrawn applications, we regress *Ln(Requested loan amount), Ln(Applicant income),* and *Loan-to-income* ratio on our *Treatment* dummy. We find that applications that are withdrawn are those that are less likely to be approved, i.e., applications for larger loan amounts (Column (2)) and applications with a higher loan-to-income ratio (Column (4)). Therefore, by proactively persuading lower-quality applicants that would ultimately be rejected to withdraw their applications, branch employees could avoid disappointing and potentially losing customers, and thus preserve the bank's relationship with them. Ultimately, branch employees can guide these customers to submit a more suitable application that is likely to be approved.

## 7. Concluding Remarks

Over the past few decades, banks have become more geographically dispersed. The resulting increased distance between headquarters and its branches could exacerbate distance-agency conflicts by impeding the ability of headquarters' managers to monitor activities of branches at the local level. In this study, we investigate how proximity of branches to headquarters impacts headquarters' monitoring stringency and its effects on branch outputs and efficiency.

We proxy headquarters-to-branch proximity using travel time, and exploit the staggered introductions of new flight routes to identify reductions in travel time between headquarters and bank branches in order to investigate its effects on branch mortgage lending. We posit that the travel time saving brought about by the new flight routes increases the frequency and likelihood that headquarters' managers would visit and monitor local branches. We find that reducing headquarters-branch travel time by at least one hour leads to a 5.5% increase in mortgage origination volume in the branch's county. Further, loans originated after treatment are 1.7% less likely to default. Being able to link headquarters' monitoring to the ex-post performance of individual mortgage loans represents a particularly novel and significant aspect of our paper. This allows us to show, for the first time, that increased internal monitoring within banks leads to superior local lending outcomes. This finding constitutes an important contribution of our work, given the limited empirical evidence regarding the impact of internal monitoring within banks on local lending performance.

While we acknowledge that we cannot directly observe the actual monitoring visits of headquarters' managers, we provide additional circumstantial evidence that supports our conjecture. Specifically, we find that headquarters' managers are more likely to exploit reductions in travel time to visit local branches when they are more constrained and when the treated branches are more important to the bank. Further, exploiting the granularity of the mortgage data, we document two non-mutually exclusive channels through which reducing headquarters-branch travel time leads to increases in lending volume and loan performance in treated branches. We find that following treatment, branch employees work harder to seek new customers as well as perform more rigorous loan screening. Overall, our findings support the hypothesis that geographic proximity between headquarters and local branches reduces distance-related agency frictions.

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**Figure 1: Distance Between Bank's Headquarters and Bank Branches**

This figure displays the average distance between a bank's headquarters and its branches and the total number of branches of all banks during the sample period from 1994 to 2021.

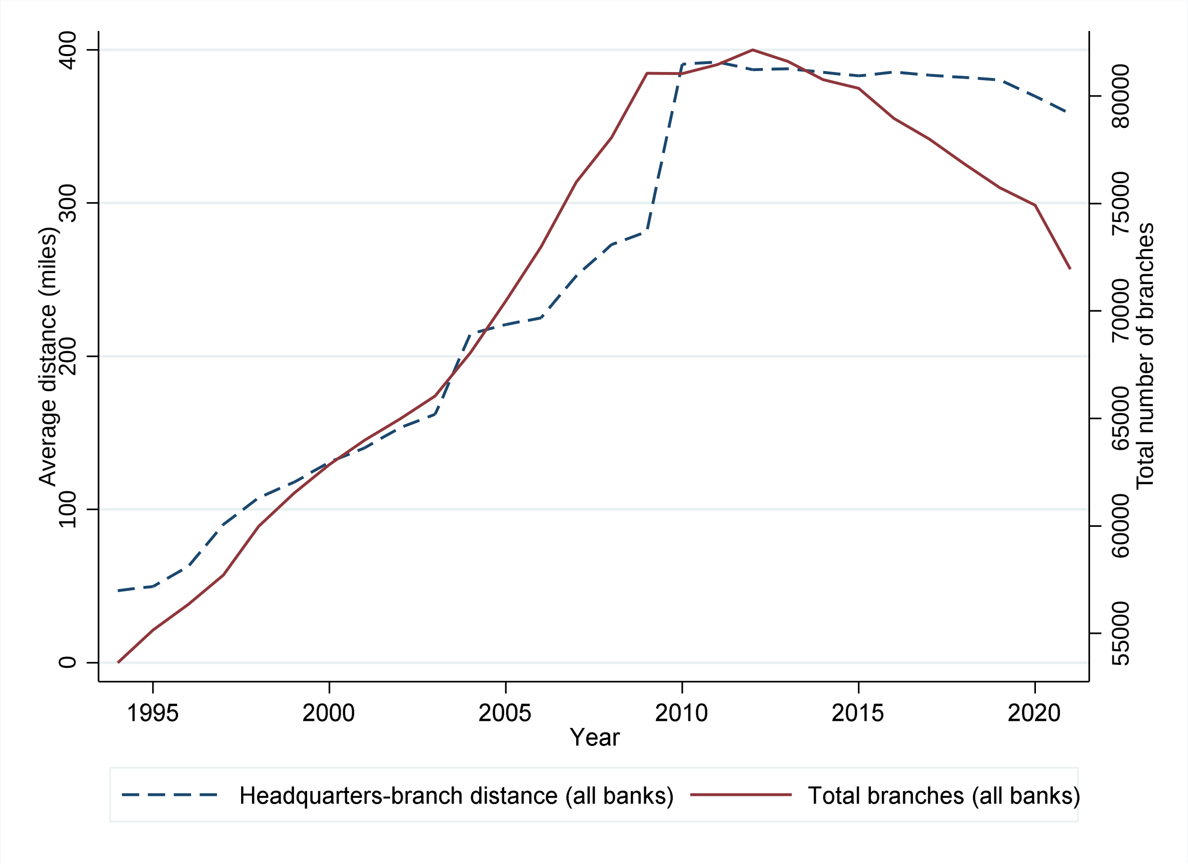
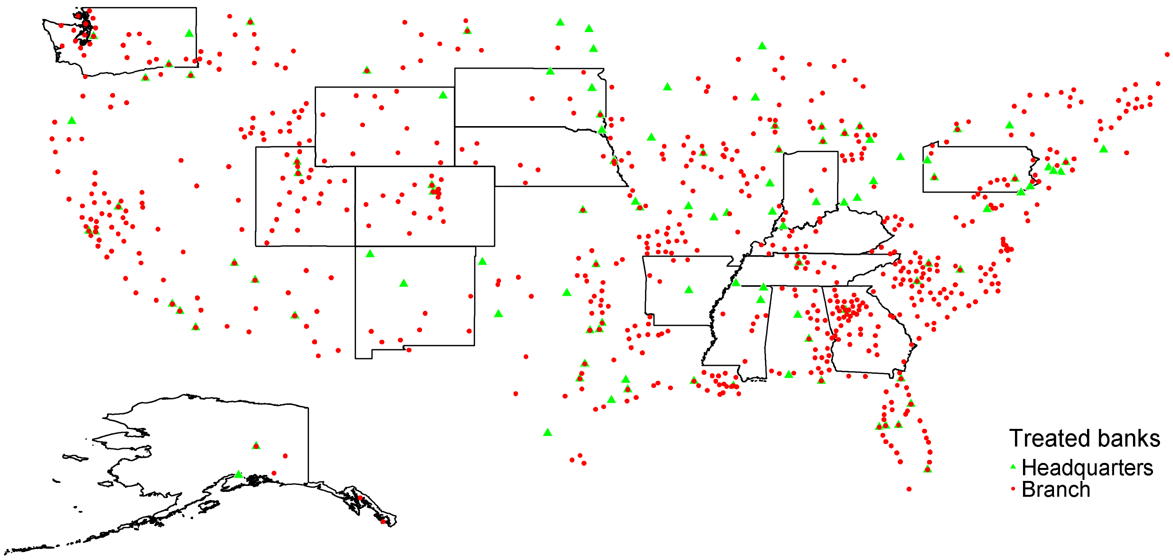


**Figure 2. Geographical Distribution of Treated Locations 1994–2021**

This figure displays the geographical distribution of treated bank headquarters-branch county pairs during the sample period from 1994 to 2021. The green triangles indicate treated banks' headquarters while the red dots indicate treated bank branches.



## Table 1 Summary Statistics

This table reports the summary statistics for the loan-level, bank-level, and bank-county-year variables included in the main analyses. Refer to Appendix 1 for the definition and construction of variables used in this study.

| Variables | N | Mean | Std. | p1 | p50 | p99 |
|---|---|---|---|---|---|---|
| ***Loan-level characteristics*** | | | | | | |
| Treatment | 8,105,272 | 0.042 | 0.201 | 0.000 | 0.000 | 1.000 |
| Approved | 8,105,272 | 0.761 | 0.426 | 0.000 | 1.000 | 1.000 |
| Ln(Requested loan amount) | 8,105,272 | 4.507 | 1.219 | 1.099 | 4.682 | 6.948 |
| Ln(Applicant income) | 8,105,272 | 4.298 | 0.793 | 2.565 | 4.263 | 6.482 |
| Loan-to-income | 8,105,272 | 1.922 | 7.147 | 0.056 | 1.579 | 6.842 |
| Female | 8,105,272 | 0.261 | 0.439 | 0.000 | 0.000 | 1.000 |
| African American | 8,105,272 | 0.059 | 0.236 | 0.000 | 0.000 | 1.000 |
| Asian | 8,105,272 | 0.047 | 0.211 | 0.000 | 0.000 | 1.000 |
| Other Non-white | 8,105,272 | 0.137 | 0.343 | 0.000 | 0.000 | 1.000 |
| Improve | 8,105,272 | 0.175 | 0.380 | 0.000 | 0.000 | 1.000 |
| Refinance | 8,105,272 | 0.494 | 0.500 | 0.000 | 0.000 | 1.000 |
| FHA | 8,105,272 | 0.043 | 0.203 | 0.000 | 0.000 | 1.000 |
| VA | 8,105,272 | 0.012 | 0.108 | 0.000 | 0.000 | 1.000 |
| FSA/RHS | 8,105,272 | 0.004 | 0.066 | 0.000 | 0.000 | 0.000 |
| Ln(# applications bank-county-year) | 8,105,272 | 4.329 | 1.573 | 1.099 | 4.234 | 7.963 |
| Ln(#applications bank-year) | 8,105,272 | 7.777 | 2.711 | 2.079 | 7.936 | 11.840 |
| Ln(Loan amount) | 6,168,203 | 4.625 | 1.153 | 1.386 | 4.787 | 6.972 |
| Delinquent | 189,586 | 0.040 | 0.197 | 0.000 | 0.000 | 1.000 |
| Loan-to-value | 189,586 | 74.760 | 14.520 | 27.000 | 79.000 | 97.000 |
| FICO | 189,586 | 756.900 | 44.910 | 635.000 | 769.000 | 817.000 |
| ***Bank-level characteristics*** | | | | | | |
| Ln(Assets) | 8,105,272 | 17.490 | 2.991 | 11.600 | 17.820 | 21.560 |
| Midsize bank | 8,105,272 | 0.342 | 0.474 | 0.000 | 0.000 | 1.000 |
| Large bank | 8,105,272 | 0.495 | 0.500 | 0.000 | 0.000 | 1.000 |
| ROA | 8,105,272 | 0.010 | 0.007 | -0.012 | 0.011 | 0.024 |
| Loan/Assets | 8,105,272 | 0.623 | 0.128 | 0.270 | 0.637 | 0.884 |
| Deposits/Assets | 8,105,272 | 0.722 | 0.114 | 0.380 | 0.729 | 0.910 |
| ***Bank-county-year characteristics*** | | | | | | |
| Branch loan amount/Bank loan amount | 457,926 | 0.218 | 0.327 | 0.000 | 0.043 | 1.000 |
| Branch customers/Bank customers | 457,926 | 0.218 | 0.330 | 0.000 | 0.039 | 1.000 |
| Ln(# applications bank-county-year) | 457,926 | 4.247 | 1.509 | 0.693 | 4.248 | 7.997 |
| Ln(Total requested loan amount bank-county-year) | 457,926 | 8.933 | 1.779 | 4.190 | 8.939 | 13.360 |
| %non-white applicants | 457,926 | 0.233 | 0.222 | 0.000 | 0.170 | 1.000 |
| %female applicants | 457,926 | 0.223 | 0.122 | 0.000 | 0.220 | 0.579 |
| %conventional loans | 457,926 | 0.936 | 0.120 | 0.450 | 1.000 | 1.000 |
| %refinance | 457,926 | 0.429 | 0.217 | 0.000 | 0.424 | 1.000 |

**Table 2: Mortgage Lending Volume**

This table presents loan-level regressions on the effect of travel time reductions on mortgage lending volume. The dependent variable is *Approved*, a dummy variable that equals one if a loan was approved and zero otherwise. *Treatment* is a dummy that equals one if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank's headquarters and branches in a county by at least one hour. Appendix 1 displays variable definitions. Standard errors are clustered at the county-year level and are reported in brackets. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

| **Dependent variables:** | *Approved* | *Ln(Loan amount)* | *Approved* | *Approved* |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| **Treatment** | **0.009**** | **0.015**** | **0.042***** | |
| | **[0.005]** | **[0.007]** | **[0.006]** | |
| Pre2 | | | | -0.0001 |
| | | | | [0.008] |
| Pre1 | | | | 0.0003 |
| | | | | [0.009] |
| Zero | | | | 0.027*** |
| | | | | [0.007] |
| Post1 | | | | 0.044*** |
| | | | | [0.009] |
| Post2plus | | | | 0.045*** |
| | | | | [0.006] |
| Ln(Assets) | 0.007*** | -0.012*** | 0.013*** | 0.013*** |
| | [0.002] | [0.004] | [0.002] | [0.002] |
| Midsize Bank | -0.001 | 0.001 | -0.005** | -0.004** |
| | [0.002] | [0.004] | [0.002] | [0.002] |
| Large Bank | -0.025*** | -0.015* | -0.039*** | -0.039*** |
| | [0.003] | [0.008] | [0.004] | [0.004] |
| ROA | 0.088* | 0.347*** | 0.267*** | 0.264*** |
| | [0.049] | [0.101] | [0.063] | [0.063] |
| Loan/Assets | 0.007 | -0.123*** | 0.029*** | 0.030*** |
| | [0.006] | [0.015] | [0.008] | [0.008] |
| Deposits/Assets | -0.143*** | 0.075*** | -0.154*** | -0.153*** |
| | [0.008] | [0.022] | [0.012] | [0.012] |
| FHA | -0.014*** | 0.194*** | -0.054*** | -0.054*** |
| | [0.001] | [0.002] | [0.002] | [0.002] |
| VA | 0.031*** | 0.357*** | 0.010*** | 0.010*** |
| | [0.002] | [0.004] | [0.002] | [0.002] |
| FSA/RHS | 0.001 | 0.254*** | -0.029*** | -0.029*** |
| | [0.002] | [0.003] | [0.003] | [0.003] |
| Improve | -0.166*** | -1.255*** | -0.164*** | -0.164*** |
| | [0.001] | [0.009] | [0.002] | [0.002] |
| Refinance | -0.048*** | -0.098*** | -0.076*** | -0.076*** |
| | [0.001] | [0.002] | [0.001] | [0.001] |
| Other Non-white | -0.111*** | -0.052*** | -0.055*** | -0.055*** |
| | [0.001] | [0.001] | [0.001] | [0.001] |
| African American | -0.140*** | -0.124*** | -0.113*** | -0.113*** |
| | [0.001] | [0.003] | [0.001] | [0.001] |
| Asian | -0.042*** | 0.057*** | -0.024*** | -0.024*** |
| | [0.001] | [0.002] | [0.001] | [0.001] |
| Female | 0.000 | -0.040*** | -0.002*** | -0.002*** |
| | [0.000] | [0.001] | [0.001] | [0.001] |
| Ln(Applicant income) | 0.095*** | 0.522*** | 0.065*** | 0.065*** |
| | [0.001] | [0.006] | [0.001] | [0.001] |
| Loan-to-income | -0.000*** | 0.016*** | -0.000*** | -0.000*** |
| | [0.000] | [0.006] | [0.000] | [0.000] |
| Ln(# of applications bank-county-year) | 0.008*** | 0.028*** | 0.003* | 0.003* |
| | [0.002] | [0.003] | [0.002] | [0.002] |
| Ln(# of applications bank-year) | 0.011*** | -0.001 | 0.009*** | 0.009*** |
| | [0.001] | [0.003] | [0.002] | [0.002] |
| Observations | 8,105,272 | 6,165,664 | 8,105,272 | 8,105,272 |
| $R^2$ | 0.161 | 0.681 | 0.117 | 0.117 |
| Weighted by loan amount | No | No | Yes | Yes |
| County-year fixed effects | Yes | Yes | Yes | Yes |
| Bank-county fixed effects | Yes | Yes | Yes | Yes |

**Table 3: Controlling for additional underwriting variables**

This table presents loan-level regressions on the effect of travel time reductions on mortgage lending volume. Panel A uses a subsample of 2018-2021 HMDA data to control for additional covariates that could affect mortgage approval decisions. Panel B additionally controls for census-tract-level averages of three underwriting variables that capture loan quality: the reported applicant's FICO score, loan-to-value ratio, and debt-to-income ratio. These variables are constructed using data from Black Knight's McDash database for loans that have been originated. *Treatment* is a dummy that equals one if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank's headquarters and branches in a county by at least one hour. Control variables are collapsed for brevity and are identical to the ones included in Table 2. Appendix 1 displays variable definitions. Standard errors are clustered at the county-year level and are reported in brackets. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

**Panel A: Controlling for additional underwriting variables available from 2018-2021 HMDA**

| **Dependent variable:** | *Approved* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Treatment | 0.027*** | 0.028*** | 0.031*** | 0.031*** |
| | [0.009] | [0.008] | [0.007] | [0.007] |
| Desktop Underwriter | | 0.155*** | 0.114*** | 0.112*** |
| | | [0.003] | [0.002] | [0.002] |
| Loan Prospector | | 0.190*** | 0.146*** | 0.144*** |
| | | [0.003] | [0.003] | [0.003] |
| TOTAL Scorecard | | 0.190*** | 0.155*** | 0.149*** |
| | | [0.007] | [0.007] | [0.007] |
| GUS | | 0.432*** | 0.368*** | 0.387*** |
| | | [0.021] | [0.021] | [0.021] |
| Ln(Property Value) | | 0.062*** | 0.048*** | 0.048*** |
| | | [0.002] | [0.001] | [0.001] |
| Loan-to-value | | 0.000 | - | - |
| | | [0.000] | - | - |
| Debt-to-income | | -0.010*** | - | - |
| | | [0.000] | - | - |
| Vantage | | 0.086*** | 0.082** | 0.081** |
| | | [0.031] | [0.032] | [0.032] |
| Equifax | | 0.031*** | 0.009*** | 0.009*** |
| | | [0.002] | [0.002] | [0.002] |
| Experian | | 0.031*** | 0.008*** | 0.008*** |
| | | [0.002] | [0.002] | [0.002] |
| FICO Risk Score | | 0.028*** | 0.006*** | 0.006*** |
| | | [0.002] | [0.002] | [0.002] |
| Applicant Age (< 45) | | 0.016*** | 0.015*** | 0.015*** |
| | | [0.001] | [0.001] | [0.001] |
| Observations | 1,303,074 | 1,189,997 | 1,189,997 | 1,189,997 |
| $R^2$ | 0.147 | 0.280 | 0.402 | 0.404 |
| Weighted by loan amount | Yes | Yes | Yes | Yes |
| County-year fixed effects | Yes | Yes | Yes | Yes |
| Bank-county fixed effects | Yes | Yes | Yes | Yes |
| Loan-to-value bin fixed effects | No | No | Yes | No |
| Debt-to-income bin fixed effects | No | No | Yes | No |
| Loan-to-value x Debt-to-income fixed effects | No | No | No | Yes |
| Control variables | Yes | Yes | Yes | Yes |

**Panel B: Controlling for census-tract underwriting variables**

| **Dependent variable** | *Approved* |
|---|---|
| | (1) |
| Treatment | 0.040*** |
| | [0.008] |
| FICO (average census-tract) | 0.0001*** |
| | [0.000] |
| LTV (average census-tract) | 0.00001 |
| | [0.000] |
| DTI (average census-tract) | -0.00003 |
| | [0.000] |
| Observations | 5,397,186 |
| $R^2$ | 0.120 |
| Weighted by loan amount | Yes |
| County-year fixed effects | Yes |
| Bank-county fixed effects | Yes |
| Control variables | Yes |

**Table 4: Lending Volume: Travel Time, Onsite Visits, and Monitoring**

This table presents loan-level regressions on the effect of travel time reductions on mortgage lending volume. Panel A controls for *Small treatment*, a dummy that equals one if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank's headquarters and branches in a county by more than 30 minutes but less than one hour (Column (1)); and *Reverse treatment*, a dummy that equals one if at some point in or before year *t*, a travel route is discontinued that increases the travel time between the bank's headquarters and branches in a county by more than one hour (Column (2)). In Panel B, we interact *Treatment* with the dollar amount of mortgage loans originated by treated branches divided by the dollar amount of mortgage loans originated in the same bank-year (Column (1)) and the number of mortgages originated by treated branches divided by the number of mortgages originated in the same bank-year (Column (2)). *Treatment* is a dummy that equals one if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank's headquarters and branches in a county by at least one hour. Control variables are collapsed for brevity and are identical to the ones included in Table 2. Appendix 1 displays variable definitions. Standard errors are clustered at the county-year level and are reported in brackets. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

**Panel A: Alternative definitions of treatment**

| **Dependent variable** | *Approved* | |
|---|---|---|
| | (1) | (2) |
| | Small travel time reductions | Large travel time increases of more than one hour |
| Small treatment | 0.002 | - |
| | [0.004] | - |
| Reverse treatment | - | -0.019*** |
| | - | [0.006] |
| Observations | 8,105,272 | 8,105,272 |
| $R^2$ | 0.117 | 0.117 |
| Weighted by loan amount | Yes | Yes |
| County-year fixed effects | Yes | Yes |
| Bank-county fixed effects | Yes | Yes |
| Control variables | Yes | Yes |

**Panel B: Monitoring Incentives**

| **Dependent variable** | *Approved* | |
|---|---|---|
| | (1) | (2) |
| Treatment*Branch loan amount/Bank loan amount | 0.422*** | - |
| | [0.073] | - |
| Branch loan amount/Bank loan amount | 0.232*** | - |
| | [0.005] | - |
| Treatment*Branch customers/Bank customers | - | 0.422*** |
| | - | [0.101] |
| Branch customers/Bank customers | - | 0.246*** |
| | - | [0.006] |
| Treatment | 0.097*** | 0.101*** |
| | [0.012] | [0.017] |
| Observations | 8,103,472 | 8,103,472 |
| $R^2$ | 0.118 | 0.118 |
| Weighted by loan amount | Yes | Yes |
| County-year fixed effects | Yes | Yes |
| Bank-county fixed effects | Yes | Yes |
| Control variables | Yes | Yes |

**Table 5: Cross-sectional variations**

This table explores the loan-level cross-sectional variations in the treatment effect of travel time reductions on mortgage lending volume. Panel A interacts T*reatment* with dummies indicating whether the applicant is *Female*, *Black*, *Asian*, or *Other Non-white.* Panel B interacts T*reatment* with dummies time periods: 1994-2007 and 2008-2021. Panel C interacts T*reatment* with dummies indicating *Banking crisis* (the subprime lending crisis 2007–2009), *Market crises* (the Russian debt crisis and Long-Term Capital Management bailout in 1998; the bursting of the dot.com bubble and the September 11 terrorist attacks in 2000–2002; and the Covid-19 pandemic in 2020–2021), and *Normal times* (i.e., the years outside these crisis periods). Definitions of *Banking crisis* and *Market Crises* are based on Berger and Bouwman (2012). Panel D interacts T*reatment* with three size class dummies: *Small Bank* (total assets ≤ $1 billion), *Midsize Bank* (total assets > $1 billion and total assets ≤ $60 billion) and *Large Bank* (total assets > $60 billion). *Treatment* is a dummy that equals one if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank's headquarters and branches in a county by at least one hour. Control variables are collapsed for brevity and are identical to the ones included in Table 2. Appendix 1 displays variable definitions. Standard errors are clustered at the county-year level and are reported in brackets. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

**Panel A: Variations across minority applicants**

| **Dependent variable:** | *Approved* | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Treatment*Female | 0.002 | | | |
| | [0.002] | | | |
| Female | -0.003*** | | | |
| | [0.001] | | | |
| Treatment*African American | | 0.016** | | |
| | | [0.007] | | |
| African American | | -0.114*** | | |
| | | [0.001] | | |
| Treatment*Asian | | | 0.008** | |
| | | | [0.004] | |
| Asian | | | -0.025*** | |
| | | | [0.001] | |
| Treatment*Other Non-white | | | | 0.002 |
| | | | | [0.003] |
| Other Non-white | | | | -0.055*** |
| | | | | [0.001] |
| Treatment | 0.042*** | 0.043*** | 0.041*** | 0.042*** |
| | [0.006] | [0.006] | [0.006] | [0.006] |
| Observations | 8,105,272 | 8,105,272 | 8,105,272 | 8,105,272 |
| $R^2$ | 0.117 | 0.117 | 0.117 | 0.117 |
| Weighted by loan amount | Yes | Yes | Yes | Yes |
| County-year fixed effects | Yes | Yes | Yes | Yes |
| Bank-county fixed effects | Yes | Yes | Yes | Yes |
| Control variables | Yes | Yes | Yes | Yes |

**Panel B: Variations over time**

| **Dependent variable** | *Approved* |
|---|---|
| | (1) |
| Treatment*1994-2007 | 0.048*** |
| | [0.008] |
| Treatment*2008-2021 | 0.042*** |
| | [0.006] |
| Observations | 8,105,272 |
| $R^2$ | 0.117 |
| Weighted by loan amount | Yes |
| County-year fixed effects | Yes |
| Bank-county fixed effects | Yes |
| Control variables | Yes |

**Panel C: Crisis versus normal time**

| **Dependent variable** | *Approved* |
|---|---|
| | (1) |
| Treatment*Banking crisis | 0.047*** |
| | [0.008] |
| Treatment*Market crises | 0.067*** |
| | [0.007] |
| Treatment*Normal times | 0.032*** |
| | [0.006] |
| Observations | 8,105,272 |
| $R^2$ | 0.117 |
| Weighted by loan amount | Yes |
| County-year fixed effects | Yes |
| Bank-county fixed effects | Yes |
| Control variables | Yes |

**Panel D: Bank size class**

| **Dependent variable** | *Approved* |
|---|---|
| | (1) |
| Treatment*Small bank | -0.043 |
| | [0.039] |
| Treatment*Midsize bank | 0.042*** |
| | [0.012] |
| Treatment*Large bank | 0.042*** |
| | [0.006] |
| Observations | 8,105,272 |
| $R^2$ | 0.117 |
| Weighted by loan amount | Yes |
| County-year fixed effects | Yes |
| Bank-county fixed effects | Yes |
| Control variables | Yes |

**Table 6: Lending Volume: Bank-county-year regressions**

This table presents bank-county-year regressions on the effect of travel time reductions on the proportion of loans originated by treated branches relative to loans originated in a given bank-year. The dependent variables are *Branch loan amount/Bank loan amount*, the total mortgage dollars originated by treated branches in a given bank-year divided by the total mortgage dollars originated in the same the bank in that year (Column (1)), and *Branch customers/Bank customers*, the number of loans originated by treated branches in a given bank-year divided by the total number of loans originated by the bank in that year (Column (2)). *Treatment* is a dummy that equals one if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank's headquarters and branches in a county by at least one hour. Appendix 1 displays variable definitions. Standard errors are clustered at the county-year level and are reported in brackets. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

| **Dependent variables** | *Branch loan amount/Bank loan amount* | *Branch customers/Bank customers* |
|---|---|---|
| | (1) | (2) |
| Treatment | 0.009*** | 0.010*** |
| | [0.001] | [0.002] |
| Ln(Assets) | 0.000 | -0.003*** |
| | [0.001] | [0.001] |
| Midsize Bank | -0.034*** | -0.036*** |
| | [0.001] | [0.001] |
| Large Bank | 0.022*** | 0.021*** |
| | [0.002] | [0.002] |
| ROA | 0.076*** | 0.082*** |
| | [0.017] | [0.019] |
| Loan/Assets | -0.073*** | -0.086*** |
| | [0.003] | [0.003] |
| Deposits/Assets | 0.064*** | 0.071*** |
| | [0.003] | [0.004] |
| %non-white applicants | 0.001 | 0.009*** |
| | [0.001] | [0.002] |
| %female applicants | -0.001 | -0.010*** |
| | [0.002] | [0.002] |
| %conventional loans | -0.031*** | -0.036*** |
| | [0.002] | [0.002] |
| %refinance | -0.001 | 0.004*** |
| | [0.001] | [0.001] |
| Ln(Avg applicant income bank-county-year) | 0.005*** | 0.019*** |
| | [0.001] | [0.001] |
| Loan-to-income bank-county-year | 0.000 | 0.000*** |
| | [0.000] | [0.000] |
| Ln(# applications bank-county-year) | -0.102*** | -0.097*** |
| | [0.001] | [0.001] |
| Ln(# applications bank-year) | 0.092*** | 0.088*** |
| | [0.001] | [0.001] |
| Observations | 457,926 | 457,926 |
| $R^2$ | 0.961 | 0.95 |
| County-year fixed effects | Yes | Yes |
| Bank-county fixed effects | Yes | Yes |

**Table 7: Loan Performance**

This table presents loan-level regressions on the effect of travel time reductions on loan delinquencies. The dependent variable is *Delinquent*, a dummy variable that equals one for an approved loan that becomes 90-day delinquent or enters foreclosure during the first two years of the loan's life and zero otherwise. *Treatment* is a dummy that equals one if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank's headquarters and branches in a county by at least one hour. Appendix 1 displays variable definitions. Standard errors are clustered at the county-year level and are reported in brackets. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

| **Dependent variable:** | *Delinquent* | | |
|---|---|---|---|
| | (1) | (2) | (3) |
| **Treatment** | -0.007*** | -0.009*** | -0.017** |
| | [0.002] | [0.003] | [0.008] |
| Ln(Assets) | -0.006*** | -0.001 | -0.015*** |
| | [0.001] | [0.001] | [0.005] |
| Midsize Bank | 0.001 | 0.000 | 0.011 |
| | [0.003] | [0.003] | [0.008] |
| Large Bank | 0.006 | -0.007 | 0.015 |
| | [0.005] | [0.006] | [0.010] |
| ROA | -0.382*** | -0.089 | -0.139 |
| | [0.085] | [0.117] | [0.124] |
| Loan/Assets | 0.020*** | -0.002 | 0.027* |
| | [0.007] | [0.008] | [0.016] |
| Deposits/Assets | -0.148*** | -0.043*** | -0.074*** |
| | [0.011] | [0.012] | [0.021] |
| Refinance | 0.005*** | 0.005*** | 0.005*** |
| | [0.001] | [0.001] | [0.001] |
| Other Non-white | -0.017*** | 0.003 | 0.003 |
| | [0.006] | [0.006] | [0.007] |
| African American | 0.006 | 0.000 | -0.001 |
| | [0.004] | [0.004] | [0.004] |
| Asian | -0.002 | -0.001 | -0.002 |
| | [0.003] | [0.003] | [0.003] |
| Female | 0.001 | 0.000 | 0.000 |
| | [0.001] | [0.001] | [0.001] |
| Ln(Applicant income) | -0.003*** | -0.003*** | -0.003*** |
| | [0.001] | [0.001] | [0.001] |
| Loan-to-income | 0.001** | 0.000 | 0.000 |
| | [0.000] | [0.000] | [0.000] |
| Ln(# applications bank-county-year) | 0.007*** | 0.003*** | 0.001 |
| | [0.001] | [0.001] | [0.002] |
| Ln(# applications bank-year) | -0.003*** | -0.002* | 0.000 |
| | [0.001] | [0.001] | [0.002] |
| FICO | -0.001*** | -0.001*** | -0.001*** |
| | [0.000] | [0.000] | [0.000] |
| Loan-to-value | 0.0002*** | 0.0003*** | 0.0003*** |
| | [0.000] | [0.000] | [0.000] |
| Observations | 192,636 | 190,937 | 189,586 |
| $R^2$ | 0.039 | 0.131 | 0.157 |
| Weighted by loan amount | Yes | Yes | Yes |
| County-year fixed effects | No | Yes | Yes |
| Bank-county fixed effects | No | No | Yes |

**Table 8: Loan Prospecting**

Panel A presents bank-county-year regressions on the effect of travel time reductions on the number and amount of loans. The dependent variables are *Ln(# applications bank-county-year)*, the natural logarithm of the number of mortgage applications received by a bank in a county-year (Column (1)); and *Ln(Total requested loan amount bank-county-year)*, the natural logarithm of the total requested loan amount received by a bank in a county-year (Column (2)). Panel B presents loan-level regressions on the effect of travel time reductions on the characteristics of submitted loans. The dependent variables are *Ln(Applicant income)*, the natural logarithm of applicant income (Column (1)) and *Loan-to-income*, the requested loan amount divided by the applicant income (Column (2)). *Treatment* is a dummy that equals one if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank's headquarters and branches in a county by at least one hour. Appendix 1 displays variable definitions. Standard errors are clustered at the county-year level and are reported in brackets; ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

**Panel A: Quantity**

| **Sample:** | **All loans** | |
|---|---|---|
| **Dependent variables** | *Ln(# applications bank-county-year)* | *Ln(Total requested loan amount bank-county-year)* |
| | (1) | (2) |
| Treatment | 0.058*** | 0.096*** |
| | [0.021] | [0.023] |
| Ln(Assets) | 0.410*** | 0.448*** |
| | [0.005] | [0.006] |
| Midsize Bank | 0.042*** | 0.066*** |
| | [0.007] | [0.008] |
| Large Bank | 0.062*** | 0.146*** |
| | [0.013] | [0.015] |
| ROA | 2.532*** | 2.968*** |
| | [0.420] | [0.504] |
| Loan/Assets | 1.284*** | 1.495*** |
| | [0.020] | [0.023] |
| Deposits/Assets | -0.235*** | -0.419*** |
| | [0.026] | [0.031] |
| %non-white applicants | -0.336*** | -0.219*** |
| | [0.011] | [0.014] |
| %female applicants | 0.199*** | -0.389*** |
| | [0.015] | [0.018] |
| %conventional loans | -1.043*** | -1.552*** |
| | [0.020] | [0.024] |
| %refinance | 0.313*** | 0.783*** |
| | [0.010] | [0.012] |
| Observations | 464,023 | 464,023 |
| $R^2$ | 0.887 | 0.882 |
| County-year fixed effects | Yes | Yes |
| Bank-county fixed effects | Yes | Yes |

| Panel B: Loan composition | | |
|---|---|---|
| **Sample:** | **All loans** | |
| **Dependent variables:** | *Ln(Applicant income)* | *Loan-to-income* |
| | (1) | (2) |
| Treatment | 0.022** | -0.743** |
| | [0.009] | [0.317] |
| Ln(Assets) | 0.023*** | 0.054 |
| | [0.005] | [0.094] |
| Midsize Bank | 0.012*** | 0.171 |
| | [0.004] | [0.121] |
| Large Bank | -0.028*** | 0.152 |
| | [0.010] | [0.121] |
| ROA | 0.371*** | 1.358 |
| | [0.138] | [2.036] |
| Loan/Assets | 0.025 | 0.317 |
| | [0.018] | [0.257] |
| Deposits/Assets | 0.135*** | 1.384*** |
| | [0.026] | [0.509] |
| FHA | -0.486*** | -0.778*** |
| | [0.004] | [0.081] |
| VA | -0.341*** | -0.157*** |
| | [0.004] | [0.054] |
| FSA/RHS | -0.653*** | -1.021*** |
| | [0.004] | [0.111] |
| Improve | -0.221*** | -1.240*** |
| | [0.004] | [0.046] |
| Refinance | -0.086*** | -0.228*** |
| | [0.002] | [0.031] |
| Other Non-white | -0.010*** | 0.206** |
| | [0.003] | [0.082] |
| African American | -0.264*** | -0.543*** |
| | [0.004] | [0.041] |
| Asian | -0.073*** | -0.070** |
| | [0.004] | [0.035] |
| Female | -0.342*** | -0.619*** |
| | [0.002] | [0.055] |
| Ln(Applicant income) | - | -2.396*** |
| | - | [0.122] |
| Loan-to-income | -0.005*** | - |
| | [0.001] | - |
| Ln(# applications bank-county-year) | -0.020*** | -0.067 |
| | [0.004] | [0.060] |
| Ln(# applications bank-year) | -0.045*** | -0.223*** |
| | [0.003] | [0.080] |
| Observations | 9,286,445 | 9,279,298 |
| $R^2$ | 0.288 | 0.032 |
| Weighted by loan amount | Yes | Yes |
| County-year fixed effects | Yes | Yes |
| Bank-county fixed effects | Yes | Yes |

**Table 9: Loan Screening**

This table presents loan-level regressions on the effect of travel time reductions on withdrawn loans. The dependent variables are *Withdrawn,* a dummy variable that equals one if a loan was withdrawn and zero otherwise (Column (1)); *Ln(Requested loan amount),* the natural logarithm of applicant income for withdrawn loans (Column (2)); *Ln(Applicant income),* the natural logarithm of applicant income for withdrawn loans (Column (3)); and *Loan-to-income*, the requested loan amount divided by applicant income (Column (4)). *Treatment* is a dummy that equals one if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank's headquarters and branches in a county by at least one hour. Appendix 1 displays variable definitions. Standard errors are clustered at the county-year level and are reported in brackets. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

| **Samples:** | **Withdrawn and Rejected loans** | **Withdrawn loans** | | |
|---|---|---|---|---|
| **Dependent variables:** | *Withdrawn* | *Ln(Requested loan amount)* | *Ln(Applicant income)* | *Loan-to-income* |
| | (1) | (2) | (3) | (4) |
| Treatment | 0.115*** | 0.052*** | -0.022 | 0.273*** |
| | [0.014] | [0.016] | [0.030] | [0.071] |
| Ln(Assets) | -0.038*** | -0.049*** | -0.023 | 0.128 |
| | [0.006] | [0.011] | [0.017] | [0.141] |
| Midsize Bank | 0.037*** | -0.003 | 0.021 | 0.05 |
| | [0.007] | [0.014] | [0.025] | [0.098] |
| Large Bank | 0.026** | -0.054** | 0.04 | 0.008 |
| | [0.012] | [0.021] | [0.036] | [0.145] |
| ROA | 1.049*** | 0.867*** | 1.042** | 5.692* |
| | [0.213] | [0.242] | [0.415] | [2.935] |
| Loan/Assets | 0.297*** | -0.294*** | -0.068 | -0.707* |
| | [0.019] | [0.045] | [0.055] | [0.367] |
| Deposits/Assets | -0.166*** | 0.081* | 0.194*** | 0.127 |
| | [0.021] | [0.047] | [0.063] | [0.317] |
| FHA | -0.063*** | 0.028*** | -0.461*** | -0.093** |
| | [0.002] | [0.004] | [0.010] | [0.041] |
| VA | -0.039*** | 0.155*** | -0.335*** | 0.204*** |
| | [0.003] | [0.008] | [0.015] | [0.068] |
| FSA/RHS | -0.089*** | 0.034** | -0.654*** | -0.005 |
| | [0.005] | [0.013] | [0.023] | [0.072] |
| Improve | -0.106*** | -0.602*** | -0.224*** | -0.922*** |
| | [0.002] | [0.017] | [0.011] | [0.030] |
| Refinance | -0.083*** | -0.097*** | -0.136*** | -0.238*** |
| | [0.001] | [0.004] | [0.005] | [0.020] |
| Other Non-white | -0.021*** | -0.045*** | -0.016*** | -0.024 |
| | [0.001] | [0.003] | [0.006] | [0.032] |
| African American | -0.059*** | -0.069*** | -0.246*** | -0.226*** |
| | [0.002] | [0.006] | [0.009] | [0.032] |
| Asian | 0.004 | 0.015*** | -0.070*** | 0.03 |
| | [0.002] | [0.004] | [0.008] | [0.035] |
| Female | -0.003*** | -0.035*** | -0.306*** | -0.087*** |
| | [0.001] | [0.002] | [0.006] | [0.027] |
| Ln(Applicant income) | 0.060*** | 0.560*** | - | -1.092*** |
| | [0.001] | [0.013] | - | [0.058] |
| Loan-to-income | 0.000 | 0.038*** | -0.037*** | - |
| | [0.000] | [0.013] | [0.012] | - |
| Ln(# applications bank-county-year) | -0.016*** | 0.042*** | 0.019 | -0.005 |
| | [0.004] | [0.010] | [0.013] | [0.063] |
| Ln(# applications bank-year) | 0.019*** | -0.004 | -0.043*** | 0.012 |
| | [0.004] | [0.007] | [0.011] | [0.054] |
| Observations | 2,433,817 | 489,269 | 489,269 | 489,269 |
| $R^2$ | 0.211 | 0.719 | 0.413 | 0.438 |
| Weighted by loan amount | Yes | Yes | Yes | Yes |
| County-year fixed effects | Yes | Yes | Yes | Yes |
| Bank-county fixed effects | Yes | Yes | Yes | Yes |

## Appendix 1. Variable Construction and Definitions

| Variable | Definition | Source |
|---|---|---|
| ***Key explanatory Variables*** | | |
| Treatment | A dummy that equals one if at some point in or before year *t*, a new travel route that reduces the travel time between the bank's headquarters and branches in a county by at least one hour is initiated. | Various sources |
| Small treatment | A dummy that equals one if at some point in or before year *t*, a new travel route that reduces the travel time between the bank's headquarters and branches in a county by more than 30mins but less than one hour is initiated. | Various sources |
| Reverse treatment | A dummy that equals one if at some point in or before year *t*, a discontinued travel route that increases the travel time between the bank's headquarters and branches in a county by at least one hour occurs. | Various sources |
| ***Loan-level variables*** | | |
| Approved | A dummy variable that equals one if a loan is approved and zero otherwise | HMDA |
| Withdrawn | A dummy variable that equals one if a loan is withdrawn and zero if it is rejected | HMDA |
| Ln(Requested loan amount) | The natural logarithm of the requested loan amount | HMDA |
| Ln(Loan amount) | The natural logarithm of the approved loan amount | HMDA |
| Ln(Applicant income) | The natural logarithm of the applicant's income | HMDA |
| Loan-to-income | Requested loan amount to income of applicants | HMDA |
| Female | A dummy variable that equals one if the applicant is female | HMDA |
| African American | A dummy variable that equals one if the applicant is African American | HMDA |
| Asian | A dummy variable that equals one if the applicant is Asian | HMDA |
| Other Non-white | A dummy variable that equals one if the applicant is American Indian, Alaska Native, Native Hawaiian, or Other Pacific Islander | HMDA |
| FHA | A dummy variable that equals one if the loan is insured by the Federal Housing Administration | HMDA |
| VA | A dummy variable that equals one if the loan is guaranteed by Veterans Administration | HMDA |
| FSA/RHS | A dummy variable that equals one if the loan is guaranteed by the Farm Service Agency or Rural Housing Service. | HMDA |
| Improve | A dummy that equals one if the loan's purpose is for home improvement | HMDA |
| Refinance | A dummy that equals one if the loan's purpose is for refinancing | HMDA |
| Equifax | A dummy that equals one if the credit's scoring model is Equifax | HMDA |
| Experian | A dummy that equals one if the credit's scoring model is Experian | HMDA |
| FICO risk score | A dummy that equals one if the credit's scoring model is FICO Risk Score Classic 04 or FICO Risk Score Classic 98 | HMDA |
| Vantage | A dummy that equals one if the credit's scoring model is Vantage Score 2.0 or Vantage Score 3.0 | HMDA |
| Desktop Underwriter | A dummy that equals one if the automated underwriting system used is Desktop Underwriter | HMDA |
| Loan Prospector | A dummy that equals one if the automated underwriting system used is Loan Prospector or Loan Product Advisor | HMDA |
| TOTAL Scorecard | A dummy that equals one if the automated underwriting system used is Technology Open to Approved Lenders (TOTAL) Scorecard | HMDA |
| GUS | A dummy that equals one if the automated underwriting system used is Guaranteed Underwriting System (GUS) | HMDA |
| Applicant Age (< 45) | A dummy that equals one if the applicant's age is below 45 | HMDA |
| Debt-to-income | Debt to income of applicants | |
| Ln(Property Value) | The natural logarithm of the property value | |
| Delinquent | A dummy that equals one if an approved loan becomes 90-day delinquent or goes into foreclosure during the first two years of the loan's life | Fannie Mae |
| Loan-to-value | Loan amount to property value | Fannie Mae |
| FICO | FICO score | Fannie Mae |

| | | |
|---|---|---|
| ***Census-tract-level variables*** | | |
| FICO (average census-tract) | The census-tract-level average of the reported applicant’s FICO score | McDash |
| LTV (average census-tract) | The census-tract-level average of the reported applicant’s loan-to-value ratio | McDash |
| DTI (average census-tract) | The census-tract-level average of the reported applicant’s debt-to-income ratio | McDash |
| ***Bank-level variables*** | | |
| Ln(Assets) | The natural logarithm of total assets | FR Y-9C |
| Small bank | A dummy variable that equals one for banks with total book assets ≤ $1 billion | FR Y-9C |
| Midsize bank | A dummy variable that equals one for banks with total book assets > $1 billion and ≤ $60 billion | FR Y-9C |
| Large bank | A dummy variable that equals one for banks with total assets > $60 billion | FR Y-9C |
| ROA | Earnings before interest and taxes divided by total assets | FR Y-9C |
| Deposits/Assets | Total deposits divided by total assets | FR Y-9C |
| Loan/Assets | Total loans divided by total assets | FR Y-9C |
| Ln(# applications bank-year) | The natural logarithm of the number of mortgage applications received by a bank in a given year | HMDA |
| ***Bank-county-year variables*** | | |
| Ln(# applications bank-county-year) | The natural logarithm of the number of mortgage applications received by a bank in a county-year | HMDA |
| Ln(Total requested loan amount bank-county-year) | The natural logarithm of the total requested loan amount received by a bank in a county-year | HMDA |
| Ln(Avg applicant income bank-county-year) | The natural logarithm of the average applicant’s income received by a bank in a county-year | |
| Loan-to-income bank-county-year | The average requested loan amount to income of applicants received by a bank in a county-year | |
| Branch loan amount/Bank loan amount | The total mortgage dollars originated by treated branches in a given bank-year divided by the total mortgage dollars originated by the bank in that year | HMDA |
| Branch customers/Bank customers | The number of loans originated by treated branches in a given bank-year divided by the total number of loans originated by the bank in that year | HMDA |
| %female applicants | The ratio of the number of applications from female applicants to the total number of applications received 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 received for each bank-county-year; non-white applicants include all applicants whose reported race is non-white | HMDA |
| %conventional loans | The ratio of the number of conventional loan applications to the total number of applications received for each bank-county-year | HMDA |
| %refinance | The ratio of the number of applications for mortgage refinancing to the total number of applications received for each bank-county-year | HMDA |

**Appendix 2: Robustness on Main Results**

This table presents loan-level regressions on the effect of travel time reductions on mortgage lending. Panel A presents a placebo test using cargo routes. Panel B restricts *Treatment* to those arising from a merger between two airlines. Panel C perform other robustness tests. We restrict the sample to loans originated in counties where the bank has only one branch in the county in Column (1); use a shorter window that ends five years after treatment in Column (2); exclude the 2007-2009 financial crisis and the 2000-2001 dot-com bubble in Columns (3) and (4), respectively. The dependent variable is *Approved*, a dummy variable that equals one if a loan was approved and zero otherwise. *Treatment* is a dummy that equals one if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank's headquarters and branches in a county. Control variables are collapsed for brevity and are identical to the ones included in Table 2. Appendix 1 displays variable definitions. Standard errors are clustered at the county-year level and are reported in brackets. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

**Panel A: Placebo test using cargo routes**

| **Dependent variable:** | *Approved* |
|---|---|
| | (1) |
| Treatment | 0.003 |
| | [0.006] |
| Observations | 7,763,568 |
| $R^2$ | 0.121 |
| Weighted by loan amount | Yes |
| County-year fixed effects | Yes |
| Bank-county fixed effects | Yes |
| Control variables | Yes |

**Panel B: Treatment as a result of airline mergers**

| **Dependent variable:** | *Approved* |
|---|---|
| | (1) |
| Treatment | 0.039*** |
| | [0.007] |
| Observations | 8,105,272 |
| $R^2$ | 0.117 |
| Weighted by loan amount | Yes |
| County-year fixed effects | Yes |
| Bank-county fixed effects | Yes |
| Control variables | Yes |

**Panel C: Other robustness tests**

| **Dependent variable:** | *Approved* | | | |
|---|---|---|---|---|
| | (1)<br>Counties that treated banks have one branch | (2)<br>Shorter window after treatment | (3)<br>Exclude 2007-09 crisis | (4)<br>Exclude 2000-01 dot-com bubble |
| Treatment | 0.025** | 0.036*** | 0.033*** | 0.043*** |
| | [0.011] | [0.007] | [0.006] | [0.006] |
| Observations | 7,776,179 | 8,105,272 | 7,192,086 | 7,595,986 |
| $R^2$ | 0.121 | 0.117 | 0.116 | 0.116 |
| Weighted by loan amount | Yes | Yes | Yes | Yes |
| County-year fixed effects | Yes | Yes | Yes | Yes |
| Bank-county fixed effects | Yes | Yes | Yes | Yes |
| Control variables | Yes | Yes | Yes | Yes |

*Internet Appendix*

# Proximity to Bank Headquarters and Branch Efficiency: Evidence from Mortgage Lending

This version: 2 July 2023

## 1. Loans requiring low versus high inputs

In Internet Appendix IA1, we split our 2018-2021 HMDA sample into mortgages that require low versus high inputs based on the application's AUS code. Following Frame *et al.* (2022), we label an application as a "low inputs" case if the average approval rate associated with the application's AUS code is greater than 90%. Applications with AUS codes with less than 90% approval rates are deemed to be "high inputs."[27] In other words, mortgages that require higher inputs from branch employees are cases that are less straightforward to verify, codify, and input loan and applicant details into the system for mortgage approval recommendations.

Internet Appendix IA1 reports the results. We find that the treatment effect is positive and statistically significant in cases that require high inputs from branch-level officers (Column (1)). This indicates that reductions in headquarters-to-branch travel time are especially important in facilitating lending to mortgages that require greater inputs from branch-level employees. In contrast, the treatment effect is insignificant (albeit positive) for low-input cases (Column (2)). Because decisions on these loans are mostly automatic, increased headquarters' monitoring is less likely to play a role in facilitating lending to these loans.

## References

Frame, W. S., Huang, R., Mayer, E. J., & Sunderam, A. (2022). The impact of minority representation at mortgage lenders *National Bureau of Economic Research Working Paper* Number w30125.

[27] The 90% threshold is based on the finding in Frame *et al.* (2022) that there is a sharp break in the distribution of approval rates around this threshold.

**Internet Appendix IA1: Loans requiring high versus low inputs**

This table presents loan-level regressions on the effect of travel time reductions on mortgage lending. The regressions are based on 2018-2021 HMDA data. We split the sample into mortgages that require high inputs (Column (1)) and mortgages that require low inputs (Column (2)). A mortgage application is labelled as "high input" if the average approval rate associated with the application's AUS code is less than 90%. A mortgage application is labelled as "low input" if the average approval rate associated with the application's AUS code is greater than 90%. The dependent variable is *Approved*. *Treatment* is a dummy that equals one if at some point in or before year *t*, a new travel route is initiated that reduces the travel time between the bank's headquarters and branches in a county. Control variables are collapsed for brevity and are identical to the ones included in Table 2. ***, **, and * indicate significance at the 1, 5, and 10% level, respectively.

| **Dependent variable:** | *Approved* | |
|---|---|---|
| | (1) | (2) |
| Sample split by: | High inputs | Low inputs |
| Treatment | 0.055*** | 0.011 |
| | [0.013] | [0.011] |
| Observations | 706,208 | 491,642 |
| $R^2$ | 0.221 | 0.127 |
| Weighted by loan amount | Yes | Yes |
| County-year fixed effects | Yes | Yes |
| Bank-county fixed effects | Yes | Yes |
| Control variables | Yes | Yes |

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