Bank Branching Strategies in the 1997 Thai Financial Crisis and Local Access to Credit*

Marc Rysman[1], Robert M. Townsend[2], and Christoph Walsh[3]

[1]Department of Economics, Boston University

[2]Department of Economics, Massachusetts Institute of Technology and NBER

[3]Department of Econometrics and Operations Research, Tilburg University and CEPR

February 2, 2023

Abstract

The effect of financial crises on bank branch location choices provides an unexplored channel by which crises affect access to credit for many years. We estimate a dynamic structural model of oligopolistic location choice for Thai banks allowing for competitive effects between rival banks. We predict the evolution of branch locations under the counterfactual scenario of no financial crisis in 1997. We find that there would have been 18.5% more branches and 9.3% more markets with at least one branch after ten years in the absence of the crisis. Furthermore, access to loans would have increased by 8.0 percentage points.

Key words: Banking, Dynamic Oligopoly, Financial Access

JEL Codes: D43, G21, L13, L80

*Townsend gratefully acknowledges research support from the University of Thai Chamber of Commerce, the Thailand Research Fund, the Bank of Thailand, Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD) (grant number R01 HD027638), and Private Enterprise Development in Low-Income Countries (PEDL) (funded by the Centre for Economic Policy Research and the Department for International Development under grant MRG002_1255). We also thank seminar participants and discussants at the ASSA meetings, Boston University, Tilburg University, NEUDC, NUS Singapore, Northwestern University, IIOC, University of Toronto, PUC Rio, the conference to honor John Rust, the Central Bank of Chile and Inter-American Development Bank workshop on the Industrial Organization in Financial Markets, and Texas A&M.

1 Introduction

Countries that suffer a financial crisis often see the real economy seriously impacted. Naturally, a major concern during a financial crisis is whether households and firms have access to credit. Since Bernanke (1983), economists have recognized the increased cost of financial intermediation through disruption of banking sector as a major factor in the impact of a crisis. A standard way to evaluate when access to credit normalizes is to look at when aggregate measures of economic activity, such as GDP, GDP growth, and interest rates, return to pre-crisis levels. However, we identify a new channel by which financial crises impact access to credit that can be much longer-lived than would be suggested by aggregate measures: local access to a physical bank branch. This channel is also particularly important for developing countries.

There is a wide literature documenting the effect of physical bank branch proximity on access to banking services.[1] Two reasons for this are lower transportation costs and lower information collection costs required to assess the viability of loans. Developing countries also typically have incomplete branching networks with significant gaps in coverage, especially in rural areas. Because financial crises particularly affect the functioning of banks, a financial crisis can cause banks to restrict the expansion of their branch networks, or even reduce the size of their networks. To the extent that banks fail to replace these branches, even after the economy recovers, the effects of the crises can be long-lived, and can negatively impact local communities long after aggregate measures of growth suggest the effects of the crisis are over.

We explore this issue in Thailand, which suffered a major financial crisis in 1997. Aggregate measures of economic activity recovered relatively quickly. For instance, GDP and unemployment returned to pre-crisis levels within two to three years. While GDP growth never again reached the world-leading levels that Thailand saw before the crisis, GDP growth still returned to high levels within a few years. However, we show that the crisis had a long-term

[1] See, for example, Nguyen (2019); Agarwal and Hauswald (2010); Ergungor (2010); Assuncao et al. (2020); Alem and Townsend (2014); Ho and Ishii (2011); Petersen and Rajan (2002); Degryse and Ongena (2005); Crawford et al. (2018).

impact on the branching behavior of commercial banks in Thailand. Entry of new branches fell dramatically for several years after the crisis and, for essentially the first time in Thailand's history, we observe the closure of bank branches. We argue that the lack of liquidity during the crisis forced banks to close branches in rural areas that would have otherwise been profitable in the long run. That is, profits for branches fell everywhere, which particularly led branches in rural areas over the threshold for closure, causing long-term impacts in these geographic areas. As we document, even when entry rates recovered, entry was not always in the places that saw exit. Several communities that experienced exit still have not seen new entry ten years after the crisis. Because the areas that experienced long-term closures are rural, they make up a small share of GDP and their low growth would be difficult to detect with aggregate data, but the impact on these communities is still a significant loss.

Studying the impact of the crisis on branch locations is challenging because there are many large banks in Thailand that have many branches throughout the country. These banks may interact in complex ways that are difficult to describe with simple statistics. To provide a more concrete measure of the impact of the crisis on branch locations, we specify a dynamic structural model of the bank branch location problem and estimate the model using data on branch locations obtained from the Bank of Thailand.

In our model, banks choose whether or not to enter in a large number of heterogeneous locations around Thailand. Branch profits depend on the number of branches of their own and rival banks in the same market. We assume that branches beyond a distance threshold do not affect a branch's profits, which allows us to cluster branching locations into separate markets, similar to Zheng (2016). Banks form expectations about the shocks that rivals will realize in the future and account for the benefit of preempting rivals in their branching strategies. Branch profits also depend on local demand, which we measure using the intensity of nighttime light surrounding branch locations. We intercalibrate the temporal variation in nighttime light such that our measure of local demand matches changes in real GDP on aggregate. We also allow for the banks' branching strategies to impact the growth rate of local demand, an effect documented by Jayaratne and Strahan (1996), Fulford (2015), Nguyen (2019) and Young (2021). Banks take into account their own and rivals' impacts on local demand in their branching strategies. We assume the financial crisis in 1997 arrives unexpectedly for the banks and we allow their strategies and expectations to change in response to the crisis.

As our environment is nonstationary, we assume the model has a finite horizon and estimate the model using backward induction. We control for persistent market-level unobserved heterogeneity by partitioning markets into ten different types. We follow an approach similar to Collard-Wexler (2013) and Lin (2015) to group markets. In our framework, the equilibrium choice probabilities are allowed to differ across market types and across banks.

In both our reduced-form and structural results, we find that banks prefer to locate their branches in areas with higher local demand and away from their own and rival branches. Although the financial crisis of 1997 lowered our measure of local demand in most markets, we also include an additional indicator for the crisis in the banks' profit functions. This indicator captures the change in profits that is not captured by the observed changes in our measure of local demand, such as how the liquidity crisis affected the banks' branching strategies. We estimate a large negative value for this crisis indicator, which makes banks less likely to open new branches and more likely to close existing branches. We also interact this indicator with our measure of local demand, and find that the crisis-induced losses are larger in more affluent markets.

Our model provides an explanation for why closed branches were not rebuilt after the crisis. We find that the cost of entry is a large multiple of a branch's typical annual profits. In the high-growth period of the late 1980s and early 1990s, it was optimal for banks to open branches in many rural areas, despite this large entry cost. However, the banks' losses and liquidity issues during the crisis forced them to close branches in many locations. After the crisis, our model finds that branches in many of these locations would still have been profitable if that branch had made it through the crisis. However, we find the lower growth rate after the crisis meant it was no longer worthwhile to pay the large sunk cost of entry again in those locations. Furthermore, the worsened financial access in these locations may also have contributed to lower local demand, which would have made it even less attractive to reopen branches. Therefore, these locations that lost their branches experienced a long-lasting, scarring effect of the crisis. If the branches were supported for the duration of the crisis, the bank would have optimally retained those branches in many of these locations after the economy recovered.

Our structural model is able to closely match the aggregate expansion and contraction patterns of the branching network observed in our data. We use the estimated structural model to simulate different counterfactual experiments. First, we simulate the bank branch locations that would have been chosen if there had never been a crisis in 1997, quantifying the effect of the crisis on the bank branch network. We do this by setting the crisis indicator in banks' profit functions to zero and removing the fall in local demand during the crisis. We find that the expansion of the branch network would have followed a path similar to the pre-crisis period and would not have experienced a contraction. Ten years after the crisis, there would have been 18.5% more branches had the crash not occurred. This is significant, as the number of bank branches and bank competition has been linked to improved financial access.[2] We also find that there would have been 9.3% more markets served by at least one branch, and the average distance to the nearest branch would have fallen by 31.2% after 10 years had the crisis not occurred.

We use the estimated effect of the distance to the nearest branch on access to commercial loans found by Ji et al. (forthcoming) to evaluate the effect of the crisis on financial access in our setting. Using their estimate with our change in distance, access to loans would have increased by 8.0 percentage points in the absence of the crisis. For markets which saw a long-term reduction in their number of branches, the change in financial access would have been 14.5 percentage points larger.[3]

[2]See, for example, Beck et al. (2004); Degryse and Ongena (2005); Love and Martínez Pería (2015); Marín and Schwabe (2019); Allen et al. (2021).

[3]Ji et al. (forthcoming) study Thai branch expansion in the pre-crisis period (1986-1996) and its role in affecting growth and inequality. In contrast, we study how the 1997 crisis affected branching strategies and quantify the effect of the crisis on financial access through

In a second counterfactual experiment, we consider the effect of a branch support subsidy during the post-crisis period on banks' branching strategies. The support we consider is one that subsidizes the crisis-induced losses for branches in vulnerable markets, which are markets that are at the brink of becoming unbanked. We assume that when there is only one branch remaining in a market that the branch receives a subsidy covering the crisis-induced losses from the crisis indicator in the profit function. The subsidy sets the branch's profits to the amount they would receive if the crisis indicator in the profit function were equal to zero. This counterfactual can also be interpreted as easing the liquidity shortages faced by these branches during the crisis. Ten years after the crisis, this subsidy increases the total number of branches by only 3.2% relative to the baseline, but increases the percentage of served markets by 6.6%. Using the change in distance to the nearest branch together with the effect estimated by Ji et al. (forthcoming), it increases financial access by 5.0 percentage points, which is only 2 percentage points lower than if the crash did not occur at all, according to our other counterfactual experiment. This result provides a rationale for such support subsidies, which were implemented in many countries during the COVID-19 crisis.

Related Literature: This paper makes contributions to three strands of literature. First, we contribute to the large literature studying the effects of financial crises (e.g. Bernanke (1983)) and competition (Beck et al., 2004; Degryse and Ongena, 2005; Love and Martínez Pería, 2015; Marín and Schwabe, 2019; Allen et al., 2021) on access to credit. Bernanke (1983) pioneered the literature on the non-monetary effects of financial crises and emphasized bank closures and bank unwillingness to lend. His paper still uses aggregate measures of economic activity to characterize these effects and does not mention bank branching. Our paper highlights bank branching behavior and emphasizes how aggregate economic activity measures can mask the effect of branching in rural markets. We also contribute more generally to the literature on the scarring effects of crises (Dell'Ariccia et al., 2008; Huckfeldt, 2022; Attanasio

the branching channel.

et al., 2022). We do this by studying the effects of the Thai financial crisis on financial access through the lens of a dynamic structural model of bank branch entry and exit.

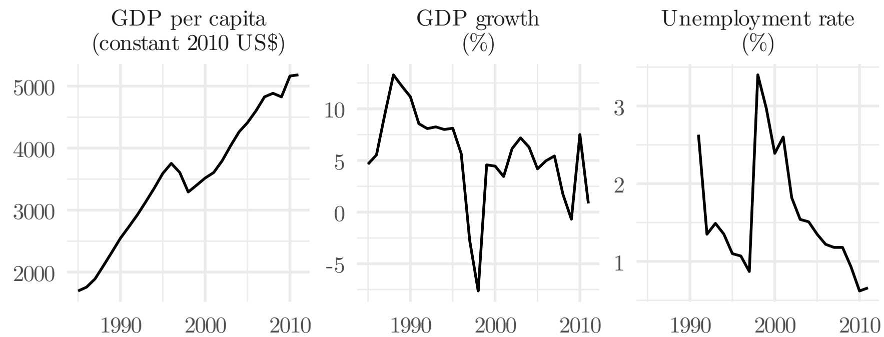
Second, we contribute to the literature on the estimation of dynamic entry models (Igami, 2017; Collard-Wexler, 2013; Lin, 2015; Zheng, 2016), but with a drastic change in environment. In our model, banks are boundedly rational in their expectations of the future arrival of the crisis. To our knowledge, the only paper modeling a drastic change such as this in a dynamic oligopoly model is Ryan (2012), who re-estimates his model of the cement industry under each policy environment.

Third, we also contribute to the growing literature using tools from empirical industrial organization to study issues related to market frictions in developing countries. Examples of markets in this literature include the Indian electricity market (Ryan, 2021), the Ghanaian radio broadcasting market (Walsh, 2020), the Columbian internet market (Hidalgo and Sovinsky, 2022) and the Ugandan garment market (Vitali, 2022). We contribute to this literature by using a dynamic entry model to study the effects of the Thai financial crisis on the banking industry and its resulting effects on financial access, an issue long-studied by the development economics literature (Banerjee et al., 2015a,b; Kaboski and Townsend, 2011).

2 Background and Data

2.1 The 1997 Financial Crisis

From 1985-1996, Thailand had the highest rate of economic growth in the world. During this time, it maintained a low inflation rate, low unemployment and a stable exchange rate. The exchange rate was tied to a basket of dominant world currencies, with a high weight on the US dollar. Thailand's high growth and stability therefore made it very attractive to foreign investors. However, a number of shocks made it difficult to maintain a fixed exchange rate. The real estate boom resulted in supply eventually exceeding demand, causing the



Data source: World Bank.

FIGURE 1: Thai macroeconomic indicators.

number of vacancies to increase and borrowers to default on their loans. The US also raised interest rates, which diverted investment away from Southeast Asia. The country then had a current account deficit for several years and the central bank's foreign reserves were insufficient to maintain a fixed exchange rate. In May 1997, with an imminent move towards a flexible exchange rate regime, there were speculative attacks from currency traders. The speculative attacks became a self-fulfilling prophecy when Thailand eventually let their currency float in July 1997. The Thai Baht immediately experienced an enormous devaluation and the economy went into crisis.

Soon after, the IMF stepped in to help stabilize the economy. Figure 1 shows GDP per capita, GDP growth and the unemployment rate during this period. GDP per capita began to fall in 1997 but returned to its pre-crisis level by 2002. GDP growth was negative for only two years and then returned to a growth rate of around 5%. Although the growth rate before the crisis reached levels of 8-12%, a growth rate of 5% is normally regarded as quite healthy. Even during the height of the crisis, unemployment reached only 3.5% and by 2002 it had fallen to 1.5%. Therefore we might conclude that Thailand recovered from the crisis within a few years. As we will see, however, the slowdown in branch openings and the closures of existing bank branches continued until 2004, and the effects of the closures were long-lived in some areas.

2.2 Bank Branch Data

We have information on the bank branches operating in Thailand from 1927-2010 from the Bank of Thailand. Our data cover all of Thailand except for the Bangkok Metropolitan and Samut Prakan provinces, which together make up the Greater Bangkok Area. For each bank branch we observe the open date, close date (if any) and GPS coordinates of the branch's location.

There are 18 different commercial banks in our data. The commercial banks combined had 3,730 bank branches across the country in 2010. In our analysis, we focus on the four largest commercial banks: Bangkok Bank, Kasikorn Bank, Krung Thai Bank and Siam Commercial Bank. These four banks constitute over two-thirds of the total number of commercial branches in our last period of data and each has significantly more branches than all of the smaller banks. Krung Thai Bank is a state-owned bank, but all four banks are publicly-traded companies. These four banks operate branches throughout the entire country. No bank is particularly dominant in any specific region.[4]

Government banks also operate in Thailand. There are two main government banks with a total of 1,928 branches at the end of 2010. These are the Government Savings Bank (GSB) and the Bank for Agriculture and Agricultural Cooperatives (BAAC), which in 2010 had 499 branches and 1,429 branches respectively. The BAAC does not tend to locate their branches in urban areas and their motives are less likely to be profit-oriented (see Assuncao et al. (2020)). The GSB, on the other hand, does locate its branches in more urban areas, with the primary aim of mobilizing savings. There is very little presence of foreign banks outside of the Greater Bangkok Area.

The 1997 financial crisis had a large effect on the commercial banks operating in Thailand. Using information from the four largest banks' annual reports, we show each bank's net profits over time in Figure 2.[5] We can see that each of the four largest banks were severely affected by the crisis and showed similar patterns. Profits remained negative for several years before recovering.

[4]We show a map of all locations held by each bank in Figure A.1 in the Online Appendix.
[5]During this time period, US$1 was on average 36.5 Thai Baht.

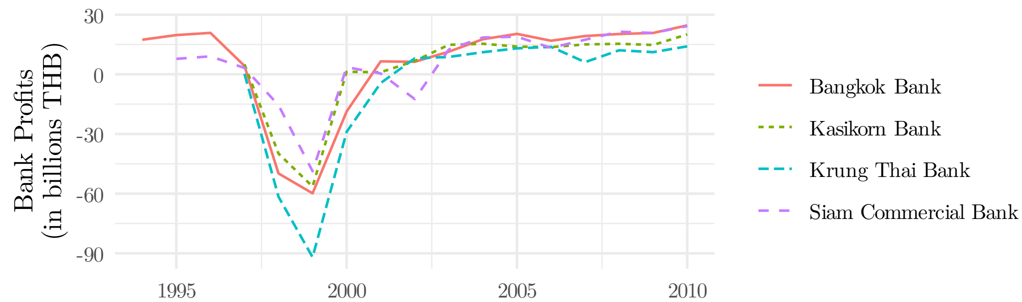


Figure 2: Net profit per bank from the banks' annual reports (in billions of Thai Baht).

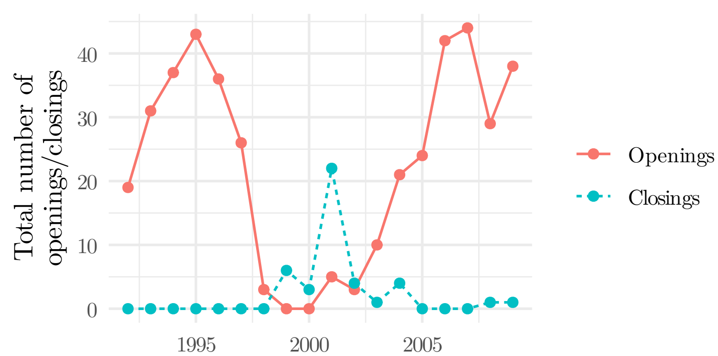


Figure 3: Number of openings and closings by year for the largest four banks.

In the years following the 1997 crisis, banks slowed the expansion of their branch networks and, for the first time in our data set (going back to 1927), there were branch closures. Figure 3 shows the total number of branch openings and closings per year from 1990 by the four largest banks in our sample. The crisis had an immediate effect on the opening of new branches and the slowdown in openings persisted until 2005. Banks also began to close branches shortly after the crisis arrived, with the first closures occurring in 1999 and peaking in 2001. According to the 1996 financial report of Siam Commercial Bank, they had anticipated opening 30 branches in 1997, but opened only 22 branches. In 1999, they stated they "slowed domestic branch expansion and

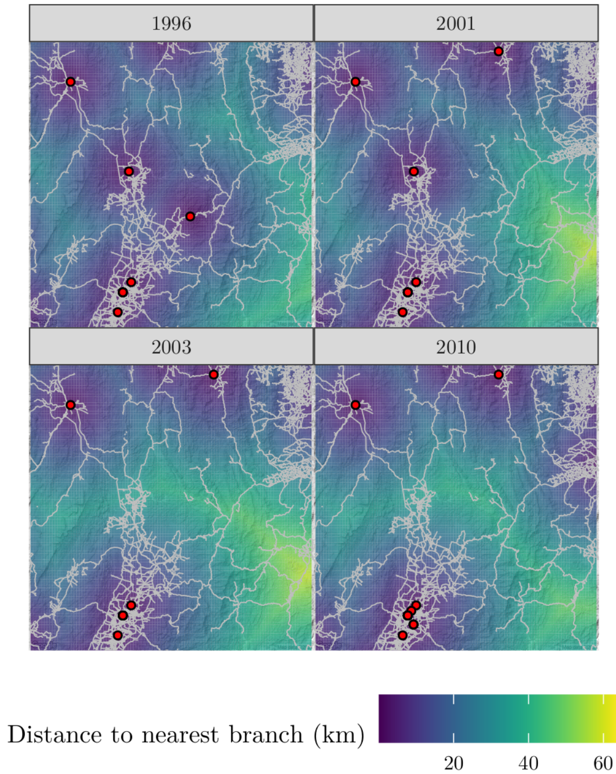


Figure 4: Distance to nearest commercial branch in the Phrae changwat following the financial crisis, 1996, 2001, 2003 and 2010.

reassessed the potential of existing branches." In their 2001 report they state they had "implemented a rationalization program" that "resulted in merging and closing down of branches."

Although branch openings began to exceed closings by 2003 on aggregate, there were many areas that saw long-lasting effects of the crisis. In locations where bank branches closed, it was many years before the bank branches were replaced, if they were replaced at all. Figure 4 shows an example area in northern Thailand that was badly affected by the crisis. The red points denote the locations of bank branches, the gray lines show the road network, and the colors in the heatmap show the distance to the nearest bank branch. Before the arrival of the crisis of 1997, the area in the center of the map was reasonably well-served by branches with most locations being within 20km of a branch.

Following the crisis, one branch closed in 2001 and another closed in 2003. Even by the end of our sample period in 2010, these locations that saw their branches close did not see a new one reopen, leaving them very far from the nearest branch. We argue that because of the positive externalities of bank branches, it was not efficient for these branches to close. The worsened financial access from losing branches can make it more difficult for households to save, smooth consumption, or make investments (Alem and Townsend, 2014). This can slow growth in these locations, making them even less attractive for banks to locate branches there in the future. Therefore, financial crisis through the bank closure channel can have long-lasting impacts on the development of these locations.

2.3 Market Definition

In our model, we assume banks make independent branching decisions market by market. Banks react to rival banks' actions within the same market, but do not react to their own or rivals' actions in other markets. Our goal, therefore, is to define markets such that banks in the same market are close competitors and there is little demand spillover between markets. Doing so is more straightforward in rural Thailand than in a developed country because banks are more disperse. Thai administrative boundaries, such as Amphoes or Tambons, are unsuitable to use as a market definition in our context as they vary greatly in size. Instead, we cluster bank branch locations based on their geographic proximity. To do this, we first take the geographic coordinates of all locations that ever had a commercial bank branch at any point in time in our data. We call these coordinates *branch locations*. These locations also include the branches of the smaller banks in our data. We define a market cluster as a group of branch locations such that every location within the market cluster is within 10km of at least one other branch location in the same cluster. For example, if a single branch location is more than 10km from every other branch location in the country, then that location is in a cluster by itself. If two branch locations are within 10km of each other but neither of the two

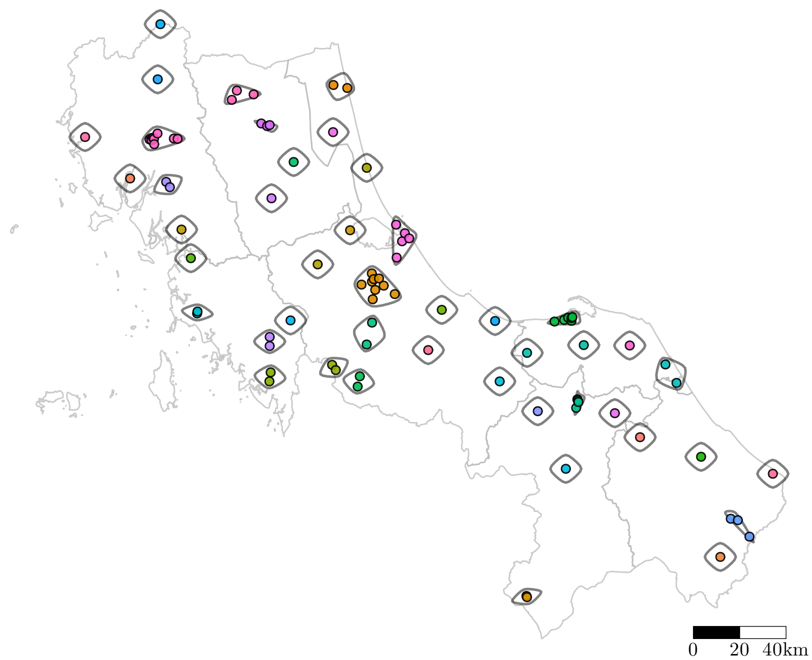


Figure 5: Clustering Locations Example in Southern Thailand

are within 10km of any other location in the country, those two locations form a single market cluster. If three branch locations were in a straight line, each 9km from each other, then all three would form a single market cluster, even though the two branches on either end are 18km away from each other.

To construct the market clusters in practice, we construct an $L \times L$ Boolean matrix where element (ℓ, ℓ') equals one if branch locations ℓ and ℓ' are within 10km of each other and is zero otherwise. We multiply this Boolean matrix by itself until it stops changing. The ℓth row of this matrix gives the locations in the same market as location ℓ.

Figure 5 shows an example of our clustering approach in the south of Thailand. Points within the same diamond that are the same color are grouped into the same market. There are a large number of markets with only one or two locations, but also some markets with many locations.

Out of the 4,128 commercial branches that were ever active in our data,

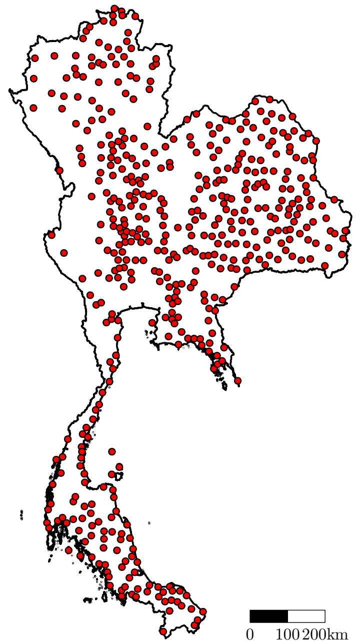


FIGURE 6: Centroid of Market Locations used in Estimation.

this approach generates 520 markets.[6] In our model, we assume that a bank in a market can open or close at most one branch per year and can have at most three branches at any given time. We therefore omit 38 markets where one of the four largest banks had more than three branches at any point in time and two additional markets where one of the banks opened more than one branch in a single year. We estimate our model with the remaining 477 markets.[7]

The locations of all the markets we use in estimation are shown in Figure 6. The average distance to the nearest other market is 21.4km and 81.8% of markets are more than 15km away from the nearest other market. We show histograms of the number of active branches and the number active banks

[6]As our data do not include the Greater Bangkok Area, we omit three markets where there was at least one branch locations within 10km of the border of either the Bangkok Metropolitan or Samut Prakan provinces.

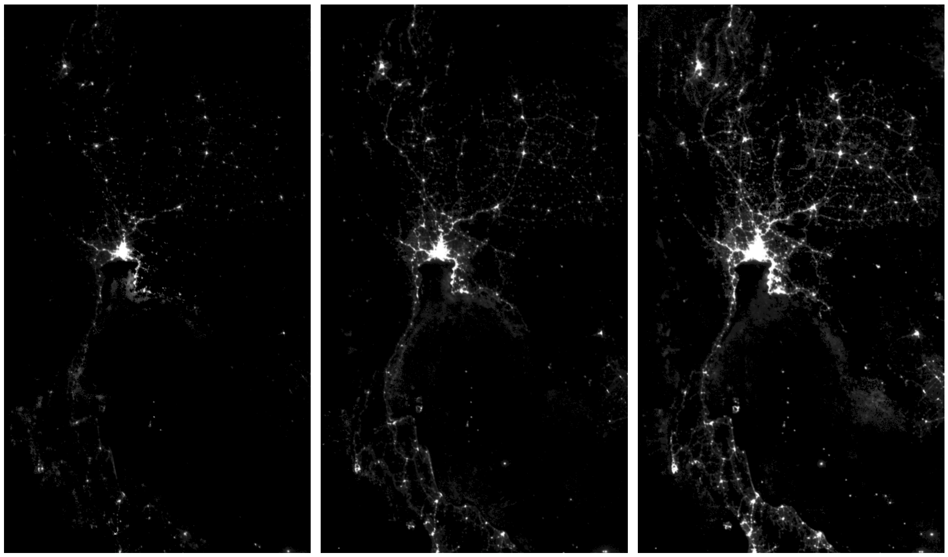
[7]The average market share of fringe banks is 0.6% in these markets. The market share of fringe banks is less than 10% in 97.5% of market-years used in estimation.

in Figure A.2 in the Online Appendix. The average number of branches in the market-years we use in estimation is 1.542 and the maximum number of branches is 10. Of the 477 markets we use in estimation, there are 74 markets where none of the four largest banks ever had a branch in our data.

Our main results are not sensitive to our threshold of 10km to construct clusters. We have repeated our entire estimation procedure and main counterfactual simulations with a larger radius of 15km radius and find only small differences. These are discussed further in Section 7.

2.4 Measuring Local Demand with GDP-Intercalibrated Nighttime Luminosity

In our model, branch profits in a market will depend on the level of local demand in the market. However, standard proxies for local demand such as population or local GDP are not readily available at a fine geographic level for Thailand. We instead use nighttime luminosity data from the National Oceanic and Atmosphere Administration to proxy market attractiveness. These data have been used as proxies for population and income in a large number of applications (see for example, Henderson et al. (2012) and Michalopoulos and Papaioannou (2013)). These data come from satellite images captured by the US Air Force at night between 8:30 PM and 10:00 PM local time around the world. These images are then processed and cleaned to represent the average amount of light emanating from a geographic location during a year. Observations obstructed by clouds are excluded, as well as observations with light coming from forest fires, gas flares, sunlight (from the summer months) and moonlight. Values are represented on a scale that ranges from 0 to 63 that measures the amount of light captured by the camera's sensor. This scale is bottom- and top-coded, with very rural locations being bottom-coded at 0 and dense urban areas being top-coded at 63. Top-coding is not a large issue in Thailand, with only 0.27% of the country being top-coded in the final year of data. Furthermore, our analysis focuses on rural areas where there is no top-coding. Data are available from 1992-2013 and are



(A) 1992 (B) 2001 (C) 2010

FIGURE 7: Raw nighttime luminosity data over time.

represented on a grid with a 30 arc-second resolution. In Thailand, one cell of the nighttime luminosity data is at a resolution of approximately 900m×900m. Because our bank branch dataset ends in 2010, we constrain our sample period in estimation to 1992-2010, the overlap of the two data sets.

Figures 7a to 7c show the nighttime luminosity in Thailand in the first, middle and last year of our sample period. The brightest area in the center is Bangkok.[8]

Because our structural model uses temporal variation in nighttime luminosity within markets, it is necessary to first intercalibrate the digital number values across years (Wu et al., 2013). The nighttime luminosity values in different years can come from satellites with different settings and the values may change over time in a location even if there is no change in luminosity. We intercalibrate the nighttime luminosity values as follows. Let Y_t be Thailand's

[8]The bright lights south of Bangkok in the Gulf of Thailand are not measurement error; rather they are from squid fishing boats that shine bright green LED lights to attract plankton to the surface. As these observations are in the sea, they are not counted in our measurement of demand.

aggregate real GDP in year t and let NL_t be the total sum of nighttime luminosity values within the country's borders in year t. When two satellite readings covering the same year are available, NL_t is the average of the two satellites. The multiplier for year t is then calculated as:

$$\kappa_t = \frac{Y_t}{NL_t}\left(\frac{\sum_{s=1992}^{2013} NL_s}{\sum_{s=1992}^{2013} Y_s}\right) \tag{1}$$

The multiplier ensures that aggregate nighttime luminosity follows the same trend as aggregate GDP and is scaled such that the sum of the intercalibrated nighttime luminosity values matches the sum of the raw values. Figure A.3 in the Online Appendix shows maps of the intercalibrated nighttime luminosity values over time.

We calculate our measure of local demand, z_{mt}, in market m at time t by drawing a circle with a radius of 20km around the centroid of branch locations within a market and summing the values of the nighttime luminosity digital numbers within that circle.[9] More specifically, let (x_m, y_m) be the longitude and latitude of the centroid of branch locations in market m and let $d\left((x,y),(x_m,y_m)\right)$ be the great-circle distance in kilometers between the pairs of coordinates (x,y) and (x_m,y_m). Local demand for a particular market m at time t is then:

$$z_{mt} = \kappa_t \int_{-90}^{90}\int_{-180}^{180} \mathbb{1}\left\{d\left((x,y),(x_m,y_m)\right) \leq 20\right\} nl_t\left(x,y\right) dxdy \tag{2}$$

where $nl_t\left(x,y\right)$ is the nighttime luminosity digital number at point (x,y) at time t.[10]

This calculation is illustrated in Figure 8. The market shown has four branch locations illustrated with four red circles. Three of the branches are located close together, whereas one of the branches is located approximately

[9] In our robustness check with a larger 15km clustering distance threshold, we increase the nighttime luminosity radius by the same proportion. That is, we use a 30km radius for calculating nighttime luminosity.

[10] We set nighttime luminosity values outside of Thailand's borders to zero before performing these calculations to avoid including the large values from the squid-fishing boats.

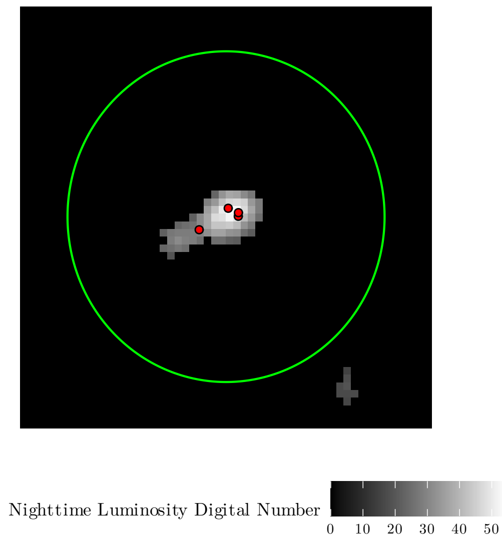


Figure 8: Night lights within a 20km radius of market centroid.

4km away to the south-west. All branches are located in an area with positive values for local demand, but are surrounded by a large area where local demand is zero. The green circle has a radius 20km around the centroid of the market. Our measure of local demand is the sum of the nighttime luminosity digital numbers in the entire circle. For the markets we use in estimation, each branch location is at most 11.8km from the market centroid, and therefore this 20km radius always includes all branch locations within the market.

To evaluate how well our local demand measure approximates local GDP, we obtain the provincial GDP data from Thailand's Office of the National Economic and Social Development Council. The province (changwat) is the smallest geographic unit where local GDP values are available. We compare provincial GDP values from 1995-2013 with the corresponding sum of intercalibrated nighttime luminosity values within a province. The two variables are have a strong correlation of 0.78. A scatter plot of the two variables is shown in Figure A.4 in the Online Appendix.

In our model, all branches entering in a market experience the same value of local demand. In our modeling, we have experimented with allowing banks to open branches in specific locations within the market cluster and allowed the value of local demand to differ by location within a market. We did this by summing the values of nighttime luminosity in a radius around each branch location rather than around the market centroid. We found that the values of local demand were highly correlated across locations within market clusters in a year. The assumption that all branches in the same market experience the same value of the local demand therefore greatly reduces the computational complexity of the model, without sacrificing substantial within-market variation in demand.

3 Model

3.1 Overview

We now describe our model for how banks make their branch-network expansion decisions. In our model, banks make independent branching decision market by market. A bank's profits from deposits and loans in a market depends on local demand, the number of branches from their own bank, and the number of branches from rival banks. The financial crisis arrives unexpectedly and has a negative effect on branch profits. Banks are forward-looking and strategic in their their branching decisions. They take into account the responses of rivals to their actions, and the effect of both their own and rivals' actions on the growth rate of local demand.

3.2 Model Setup

Banks earn profits over an infinite horizon but there is a period T after which the market state is fixed and no longer changes. Therefore, the per-period profits of active branches remain the same forever starting from period T. Time is discrete.

There are F commercial banks who can simultaneously choose to open and close branches in M different markets in each period t. Bank f has n_{fmt} active branches in market m at time t. The profit of the bank in that market is equal to:

$$\pi_f\left(\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right) = n_{fmt}\Bigg(\theta_{k(m)} + \theta_f^b + \theta^{own}\left(n_{fmt} - 1\right) + \theta^{comp}\sum_{g \neq f} n_{gmt} + \\ \theta^z z_{mt} + \theta^{crisis}\zeta_t + \theta^{crisis,z}\zeta_t \times z_{mt}\Bigg) \tag{3}$$

Each market m belongs to one of K types, and we allow the term $\theta_{k(m)}$ in the profit function to differ by market type, $k = 1, \ldots, K$. The per-branch profit also differs by bank and this is captured by θ_f^b, for $f = 2, \ldots, F$, where we make the normalization $\theta_1^b = 0$ for bank 1. The parameter θ^{own} measures the agglomeration or cannibalization effect of the bank's own branches. If $\theta^{own} > 0$, then a branch benefits from having another branch of the same bank in the same market. If $\theta^{own} < 0$, new branches cannibalize profits from its existing branches. The parameter θ^{comp} measures the competitive effect of branches of rival banks in the same market. The variable z_{mt} is a measure of local demand that affects branch profits. The variable $\zeta_t \in \{0, 1\}$ is an indicator for the financial crisis and the parameter θ^{crisis} measures the effect of the financial crisis on profits that is not captured by changes in local demand z_{mt}. This also captures the effect of the banks' lower liquidity on their payoffs; for example, if the bank cannot borrow to make additional loans. We also interact z_{mt} with ζ_t to allow markets of different sizes to be affected differently by the crisis. The market state, $\boldsymbol{s}_{mt} = \left(\{n_{fmt}\}_{f=1}^F, z_{mt}, m, t\right) \in \mathcal{S}$, is the combination of each bank's number of branches, $\{n_{fmt}\}_{f=1}^F$, local demand, z_{mt}, and the market and time period.

We assume a bank's profits within a market depend only on local demand and the presence of own and rival branches. Therefore, branch profits are independent of any of the banks' actions in other markets. Banks are also assumed to be risk neutral and have no geographic diversification motives. Supporting this assumption, Aguirregabiria et al. (2016) found that after the Riegle-Neal Act removed restrictions on branch-network expansion in the US, most banks did not take advantage of the new possibilities for geographic diversification.

These assumptions allow for the bank's national branching problem to be solved with independent branch network decisions in each market.

Now we turn to bank's beliefs about the transition process for state variables. We assume that the crisis indicator ζ_t is an exogenous deterministic function of t We assume $\zeta_t = 0$ for the periods leading up to the crisis (i.e. $t \leq 1997$), and then transitions to $\zeta_t = 1$ in the year of the crisis.[11] It stays at $\zeta_t = 1$ for seven periods, and then returns to $\zeta_t = 0$ ever after. However, before the crisis, banks do not anticipate the transition in ζ_t. We assume that in the years before the crisis, banks expect $\zeta_t = 0$ in all future time periods. Once the crisis arrives, banks have correct beliefs about ζ_t. That is, they believe $\zeta_t = 1$ until 2004. After the crisis, banks do not expect there will be another large crisis and thus believe $\zeta_t = 0$ in all future time periods (i.e. $t > 2004$).

Formally, let banks in period t believe that in period $\tau > t$, $\zeta_\tau = f_t(\tau)$, where $f_t(\tau) = 0$ for $t \leq 1997$ for all τ, $f_t(\tau) = 1$ for $t > 1997$ and $\tau \geq t$ and $\tau \leq 2004$ and $f_t(\tau) = 0$ for $t > 1997$ and $\tau > 2004$. We believe this specification of beliefs is realistic and we have found this choice produces aggregate branching patterns that best match the patterns in the data. We also test the robustness of this assumption by estimating the model assuming banks believe the crisis will last forever during the crisis years. This is discussed further in Section 7.

We also must specify bank's beliefs over the process for z_{mt}. Banks in period t believe $z_{m\tau}$ follows the Markov process $z_{m\tau+1} \sim g_t(\boldsymbol{s}_{m\tau})$ for $\tau = t, \ldots, T-1$. This specification allows beliefs to change over time in ways that banks do not anticipate. In our implementation, further discussed in Section 4.2, we assume banks believe the pre-crisis growth rates will continue forever but banks change their beliefs after the crisis takes place. Thus, we allow for $g_t(\cdot)$ to differ for $t \leq 1997$ and $t > 1997$. In this sense, our paper resembles Jeon (2022), who models firms forming beliefs about the evolution of demand based on current demand realizations. Also, by conditioning the Markov process on $\boldsymbol{s}_{mt}$, we allow the distribution of z_{mt+1} to depend on z_{mt}, market type $k(m)$, and the

[11] We assume banks make their simultaneous branching decisions at the beginning of the year (i.e. on January 1st of each year). Because the crisis began after January 1997, it did not affect the banks' branching decisions until 1998.

number of bank branches in the market. This last dependency allows the presence of banks to affect local demand growth. Finally, recall that banks in all periods t believe that $z_{m\tau+1} = z_{m\tau}$ for all $\tau \geq T$.

Aguirregabiria and Jeon (2020) survey the literature on modeling the beliefs of firms in dynamic oligopolies, covering both bounded and full rationality. Our model assumes that banks are boundedly rational in the sense that the banks' beliefs change in ways that the banks do not anticipate. Although it seems clear that the financial crisis was a surprise to Thai banks, we do not view our assumption of bounded rationality as critical to our paper. An alternative would be to allow fully rational firms to assign some relatively small probability to the arrival of a crisis and the resulting permanent change in growth rates. In this framework, the arrival of the crisis was a bad draw from this probability distribution. In our view, the data cannot distinguish between these cases and we choose the bounded rationality model only because it is easier to work with.

We now turn to the process for the number of firms in a market. We assume the set of available actions for firm f in market m at time t is to open one branch, close one branch or maintain the same number of branches. A single bank cannot open or close more than one branch in the same market in the same time period. A bank can also have at most $N = 3$ branches in a market. Denote the firm's action by $a_{fmt} \in \{-1, 0, 1\}$, where -1 denotes closing a branch, 0 denotes maintaining the same number of branches and $+1$ denotes opening a branch. The set of available actions for firm f in market m at time t, $\mathcal{A}(n_{fmt})$, therefore depends on their existing number of branches:

$$\mathcal{A}(n_{fmt}) = \begin{cases} \{0, 1\} & \text{if } n_{fmt} = 0 \\ \{-1, 0, 1\} & \text{if } n_{fmt} \in \{1, \ldots, N-1\} \\ \{-1, 0\} & \text{if } n_{fmt} = N \end{cases} \tag{4}$$

Each bank chooses to open or close branches simultaneously within a time period. Choosing to open or close a branch takes effect with a one-period lag. We can therefore write the process for a bank's number of branches in a market as $n_{fmt+1} = n_{fmt} + a_{fmt}$. If a bank chooses to open a branch, the bank incurs the entry cost θ^{ec}. The scrap value from closing a branch is normalized to zero because it would not be separately identified from the entry cost, θ^{ec}, and the constant terms, θ_k. Banks also receive action-specific private information shocks $\boldsymbol{\varepsilon}_{fmt} = \left(\varepsilon^{-1}_{fmt}, \varepsilon^{0}_{fmt}, \varepsilon^{1}_{fmt}\right)$ that affect their payoffs. We assume these private-information shocks are drawn independently from a Type I extreme value distribution.

3.3 Equilibrium

Banks are forward-looking and discount future profits with a discount factor $\beta \in (0, 1)$. The value function for bank f in market m in period T is then:

$$\widetilde{V}_f\left(\boldsymbol{s}_{mT}, \boldsymbol{\theta}\right) = \frac{\pi_f\left(\boldsymbol{s}_{mT}, \boldsymbol{\theta}\right)}{1-\beta} \tag{5}$$

The Bellman equation for bank f in market m for time periods $t < T$ is:

$$\begin{aligned} \widetilde{V}_f\left(\boldsymbol{s}_{mt}, \boldsymbol{\theta}, \boldsymbol{\varepsilon}_{fmt}\right) = \pi_f\left(\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right) + \max_{a \in \mathcal{A}\left(n_{fmt}\right)} \Bigg\{ & \varepsilon^{a}_{fmt} - \theta^{ec}\mathbb{1}\left\{a = 1\right\} \\ & + \beta \mathbb{E}\left[\widetilde{V}_f\left(\boldsymbol{s}_{mt+1}, \boldsymbol{\theta}, \boldsymbol{\varepsilon}_{fmt+1}\right) \Big| \, \boldsymbol{s}_{mt}, a_{fmt} = a\right] \Bigg\} \end{aligned} \tag{6}$$

The bank earns its flow profits in period t and, based on the realization of the private information shock $\boldsymbol{\varepsilon}_{fmt}$, chooses the action that maximizes its expected present discounted value of payoffs. The expectation over the value function integrates over bank's beliefs about rivals choices, beliefs about the presence of the crisis ζ_t (governed by $f_t(\cdot)$) and the beliefs about local demand (governed by $g_t(\cdot)$). The future transition probabilities of z_{mt} also depend on the banks' strategies, as the number of branches can impact local demand.

As the private information shocks are iid, we can integrate them out to construct a value function before the shocks are realized that does not depend on shocks. That is, $V_f\left(\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right) = \int_{\boldsymbol{\varepsilon}} \widetilde{V}_f\left(\boldsymbol{s}_{mt}, \boldsymbol{\theta}, \boldsymbol{\varepsilon}_{fmt}\right) f_{\varepsilon}\left(\boldsymbol{\varepsilon}\right) d\boldsymbol{\varepsilon}$, where f_{ε} is the joint density of the shocks. Because ε^a_{fmt} is distributed Type I extreme value, the expected value function before the realization of the private information shock is given by:

$$V_f\left(\boldsymbol{s}_{mt},\boldsymbol{\theta}\right)=\pi_f\left(\boldsymbol{s}_{mt},\boldsymbol{\theta}\right)+\quad\log\left(\sum_{a\in\mathcal{A}\left(n_{fmt}\right)}\exp\left\{-\theta^{ec}\mathbb{1}\left\{a=1\right\}+\beta\mathbb{E}\left[V_f\left(\boldsymbol{s}_{mt+1},\boldsymbol{\theta}\right)\middle|\,\boldsymbol{s}_{mt},a_{fmt}=a\right]\right\}\right) \tag{7}$$

Similarly, before the realization of the private information shock, the probability that bank f chooses action $a\in\mathcal{A}\left(n_{fmt}\right)$ in market m at time t is given by:

$$p_f\left(a_{fmt}=a\,\middle|\,\boldsymbol{s}_{mt},\boldsymbol{\theta}\right)=\frac{\exp\left\{-\theta^{ec}\mathbb{1}\left\{a=1\right\}+\beta\mathbb{E}\left[V_f\left(\boldsymbol{s}_{mt+1},\boldsymbol{\theta}\right)\middle|\,\boldsymbol{s}_{mt},a_{fmt}=a\right]\right\}}{\sum_{a'\in\mathcal{A}\left(n_{fmt}\right)}\exp\left\{-\theta^{ec}\mathbb{1}\left\{a'=1\right\}+\beta\mathbb{E}\left[V_f\left(\boldsymbol{s}_{mt+1},\boldsymbol{\theta}\right)\middle|\,\boldsymbol{s}_{mt},a_{fmt}=a'\right]\right\}} \tag{8}$$

Our solution concept is Bayesian Markov Perfect Equilibrium as in Zheng (2016). We define the strategy function of bank f in market m of type k at time t as:

$$\sigma_f\left(\boldsymbol{s}_{mt},\boldsymbol{\theta},\boldsymbol{\varepsilon}_{fmt},\widetilde{\boldsymbol{\sigma}}_{-fmt}\right)=\underset{a\in\mathcal{A}\left(n_{fmt}\right)}{\arg\max}\Big\{\pi_f\left(\boldsymbol{s}_{mt},\boldsymbol{\theta}\right)+\varepsilon^a_{fmt}-\theta^{ec}\mathbb{1}\left\{a=1\right\}+\beta\mathbb{E}\left[V_f\left(\boldsymbol{s}_{mt+1},\boldsymbol{\theta},\widetilde{\boldsymbol{\sigma}}_{-fmt+1}\right)\middle|\,\boldsymbol{s}_{mt},\widetilde{\boldsymbol{\sigma}}_{-fmt},a_{fmt}=a\right]\Big\} \tag{9}$$

The strategy function maps the current market state, $\boldsymbol{s}_{mt}$, and private information shock, $\boldsymbol{\varepsilon}_{fmt}$, into an action, $a\in\mathcal{A}\left(n_{fmt}\right)$, based on the bank's beliefs about its rivals' strategies, $\widetilde{\boldsymbol{\sigma}}_{-fmt}=\left\{\widetilde{\sigma}_{jmt}\right\}_{j\neq f}$ in the current and future time periods $t,t+1,\ldots,T-1$. In equilibrium, each bank plays according to their strategy function given their beliefs of their rivals' strategies, and each bank's beliefs are consistent with their rivals' strategies.

As we use a full-solution approach to estimation, we require that this model generates a unique equilibrium. We cannot formally guarantee uniqueness in this model. However, extensive numerical exploration of the model has not turned up any issues with convergence to multiple solutions. This is typical in full-solution models of asymmetric information, as in Seim (2006) and Augereau et al. (2006). Multiple equilibria in these models are particularly unlikely if firms have ex-ante heterogeneity within a period-market, which in our case is provided by the bank fixed effects, market type fixed effects, and banks' differing histories in entry.

4 Estimation

4.1 Market Types

Controlling for unobserved market heterogeneity is important for obtaining useful estimates from an entry model. In addition to controlling for local demand, we further allow markets to have heterogeneous market "types" that make them more or less attractive for opening bank branches. We classify each market into one of ten types following an approach similar to Collard-Wexler (2013) and Lin (2015). We do this by using the estimated market fixed effects from an ordered probit regression at the bank-market-year level. We specify the ordered probit model in a similar way to the descriptive regressions in Igami and Yang (2016). The dependent variable is the bank's action a_{fmt}, which takes on the values -1, 0 or 1 depending on if bank f closed, did nothing or opened a branch in market m in year t. For explanatory variables we include our measure of local demand, the number of the bank's own branches, the number rival branches, and a market fixed effect.

Table 1 shows the coefficient estimates from this regression. The regression shows that banks are more likely to open branches when local demand is greater. They are less likely to enter in the presence of their own branches and branches of rival banks. Figure 9 shows a histogram of the estimated market fixed effects from this regression. We divide markets into ten equally-sized categories based on the value of the estimated market fixed effects, with

Dependent variable:	Enter (1) Nothing (0) Exit (−1)
Own branches	−1.112
	(0.063)
Rival branches	−0.337
	(0.038)
Local demand	0.076
	(0.013)
Observations	34344
Market fixed effects	Yes

Standard errors in parentheses. Local demand is measured using GDP-intercalibrated nighttime luminosity in a 20km radius around the market centroid.

TABLE 1: Ordered Probit results.

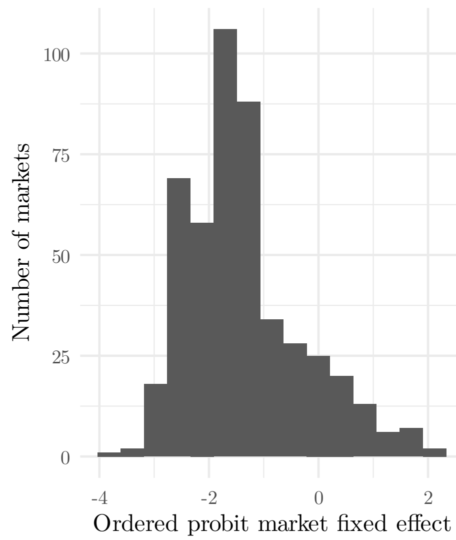


FIGURE 9: Market fixed effects

market type 1 having the smallest values.

Higher market types have more branches on average, but they do not differ on average in their level of local demand. We use the market types to capture persistent unobserved heterogeneity between markets that is not captured by our measure of local demand.

In the bank's profit function, we assume the presence of branches of the two large government banks (the BAAC and GSB) do not affect the commercial banks' profits. This is because these banks mainly serve different sectors of the market. Assuncao et al. (2020) also show that the BAAC's branching decisions are not consistent with profit maximization. We argue that our market types capture the presence of these branches and their inclusion in the banks' profit functions would not affect our main results. To test for this, we estimate an ordered probit model version of the bank's profit function using our market type fixed effects together with BAAC and GSB presence. The results are shown in Table 2. When we add the presence of BAAC or GSB branches to the baseline specification in column (1), the coefficients of the other parameters remain virtually identical and the coefficients on BAAC and GSB presence are

Dependent variable:	Enter/Nothing/Exit			
Own branches	−0.963	−0.961	−0.962	−0.960
	(0.055)	(0.055)	(0.055)	(0.055)
Rival branches	−0.165	−0.162	−0.164	−0.162
	(0.027)	(0.027)	(0.027)	(0.027)
Local demand	0.056	0.056	0.056	0.056
	(0.006)	(0.006)	(0.006)	(0.006)
BAAC presence		−0.100		−0.094
		(0.089)		(0.093)
GSB presence			−0.032	−0.014
			(0.061)	(0.063)
Crisis and Crisis × Local demand	Yes	Yes	Yes	Yes
Market type effects	Yes	Yes	Yes	Yes
Bank fixed effects	Yes	Yes	Yes	Yes
Number of observations	34344	34344	34344	34344

Standard errors in parentheses. Local demand is measured using GDP-intercalibrated night-time luminosity in a 20km radius around the market centroid. BAAC and GSB presence is measured within a 20km radius around the market centroid.

TABLE 2: Ordered Probit regression results with market types.

not statistically significant. Therefore we omit the BAAC and GSB branches from our structural model, which greatly reduces the size of our state space.

4.2 Transition Process and Beliefs for Local Demand

We now discuss our empirical specification for the transition process of local demand, z_{mt}, and the banks' beliefs about its future transitions, $g_t(\cdot)$, at each point in time. We model local demand evolving according to:

$$\begin{aligned} z_{mt+1} - z_{mt} =& \eta_{k(m)} + \eta^{post}_{k(m)} \mathbb{1}\{t > 1997\} + \alpha \sum_{f=1}^{F} n_{fmt} + \\ & \delta_{96} \mathbb{1}\{t = 1996\} + \delta_{97} \mathbb{1}\{t = 1997\} + \nu_{mt+1} \end{aligned} \tag{10}$$

where $\nu_{mt+1} \sim \mathcal{N}(0, \sigma_\nu^2)$. Local demand changes depend on the market type, k, and the number of active bank branches $\sum_{f=1}^{F} n_{fmt}$. We observe a downward shift in local demand in all markets during 1997 and 1998 which we capture with the δ_{96} and δ_{97} terms. We also allow the market type effects, $\eta_{k(m)}$, to change after the crisis by $\eta_{k(m)}^{post}$, as we observe slower growth rates in the years after the crisis.

The regression estimates of this equation are shown in Table A.1 in the Online Appendix. The regression shows that the $\eta_{k(m)}$ terms for all market types fell after the crisis. We also estimate negative coefficients on the crash years, which captures the level drop in GDP that we observe in Figure 1. The total number of active branches in a market also has a positive and significant effect on the level of local demand in the following period. We recognize the potential endogeneity issues that may arise by including the number of active branches in this regression. We take up this issue in our robustness discussion in Section 7.

We now specify the banks' beliefs, $g_t(\boldsymbol{s}_{m\tau})$, about the process for local demand in each period. Banks do not anticipate the crash to occur, nor do they anticipate the change in the transition process following the crash. That is, for $t \leq 1997$, $g_t(\boldsymbol{s}_{m\tau})$ is given by:

$$z_{m\tau+1} \sim \mathcal{N}\left(z_{m\tau} + \widehat{\eta}_{k(m)} + \widehat{\alpha}\sum_{f=1}^{F} n_{fm\tau}, \widehat{\sigma}_{\nu}^{2}\right) \tag{11}$$

for all τ, where hats denote our estimates of the parameters in the local demand transition equation. This allows the transition process to change in an unanticipated way at the time of the crisis. After the crisis arrives, banks learn the true process of local demand and believe it evolves according to the true process. That is, $g_t(\boldsymbol{s}_{m\tau})$ is given by our estimates of equation (10) for all $t > 1997$.[12]

For these estimates, we assume that there are no future growth patterns that banks know that econometricians do not driving the banks' branching decisions, or else the number of branches could be endogenous to future growth. Our market-type effects are meant to address this but we take up this issue further in our robustness discussion in Section 7.

[12] Although we assume that the crisis indicator ζ_t returns to zero after the crisis, local demand growth is permanently affected. We make this modeling choice to reflect that GDP growth never returned to pre-crisis rates.

4.3 Structural Parameter Estimation

We now discuss how we estimate our vector of structural parameters:

$$\boldsymbol{\theta} = \left(\{\theta_k\}_{k=1}^{k=10}, \left\{\theta_f^b\right\}_{f=2}^{f=4}, \theta^{own}, \theta^{comp}, \theta^{z}, \theta^{crisis}, \theta^{crisis,z}, \theta^{ec} \right) \tag{12}$$

We do not estimate the annual discount factor but set it to $\beta = 0.95$. This discount factor is commonly used in the literature for annual data (for example, Holmes (2011), Dunne et al. (2013), Collard-Wexler (2013) and Zheng (2016)).

Given a particular trial value of the structural parameters, we solve the model by backward induction. We assume the period T at which states stop changing is 25 periods in the future. Starting with period T and working backwards, we solve for the value function and equilibrium choice probabilities within each time period for each market type. Because local demand is continuous, we solve for the equilibrium choice probabilities at a fixed number of points using ten different values of local demand. We provide further details on this procedure in Online Appendix A.2. To obtain the equilibrium choice probabilities at the actual levels of local demand, we use linear interpolation.

We use maximum likelihood to estimate the structural parameters. Let $a_{fmt} \in \{-1, 0, 1\}$ be the action chosen by firm f in market m of type k at time t in the data, where the sample period is 1992 to 2009. The number of time periods we use in estimation is therefore $\widetilde{T} = 18$. The maximum likelihood estimator of $\boldsymbol{\theta}$ is then:

$$\widehat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} \sum_{t=1}^{\widetilde{T}} \sum_{m=1}^{M} \sum_{f=1}^{F} \log\left(p_f\left(a_{fmt}\,|\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right)\right) \tag{13}$$

where $p_f\left(a_{fmt}|\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right)$ is the equilibrium conditional choice probability for bank f in market m at time t in state $\boldsymbol{s}_{mt}$ given parameters $\boldsymbol{\theta}$. Our model does not require simulation.

5 Model Estimates

Table 3 shows the structural parameter estimates. The estimates show a similar pattern to the reduced-form ordered probit regression in Table 2. Branch profits are increasing in local demand and are decreasing in the presence of own and rival branches. The estimated effect of the crisis shows a large decrease in profits, much greater than the presence of rival branches. Although not statistically significant, the interaction term of the crisis with local demand shows that firms in larger, richer markets experienced a greater drop in profits. The estimated constant is monotonically increasing in the market type, in line with the values from the ordered probit market fixed effects. The estimates of the bank-specific profit shifters θ^f are close to zero except for Siam Commercial Bank. This estimate is negative relative to the base bank of Krung Thai because this is the smallest of the four largest banks.

We can use the banks' annual reports to interpret the magnitudes of the estimated parameters. The average profits per branch from our four banks in 2006 was US\$548,983. Using the average profits of active branches in 2006 according to our model, one unit in the parameter estimates is approximately US\$1.187m. Based on this value, the presence of one more rival branch on average lowers profits by US\$65,522 per year.

To show how our model fits with the data, we solve for the equilibrium strategies at the estimated structural parameters and simulate branch network expansion paths based on these strategies. Figure A.5 in the Online Appendix shows the average total number of active branches from 1,000 of such simulations. The error bars represent the 0.025 and 0.975 quantiles of the simulated network expansion paths. We can see that the predicted total number of branches matches the aggregate temporal patterns in the data relatively well, but overpredicts the number of branches in certain years. Figure A.6 in the Online Appendix shows the same but split by market type. The model matches the total number of branches by market type reasonably well. Only in market type 10 do the predicted entry paths slightly overpredict the number of branches in certain years. In Figure A.7 in the Online Appendix,

	Estimate	Standard Error
Entry cost	11.712	(0.292)
Market type 1	0.095	(0.033)
Market type 2	0.136	(0.036)
Market type 3	0.208	(0.029)
Market type 4	0.254	(0.027)
Market type 5	0.269	(0.027)
Market type 6	0.328	(0.026)
Market type 7	0.395	(0.024)
Market type 8	0.451	(0.026)
Market type 9	0.574	(0.029)
Market type 10	0.769	(0.039)
Bank 2	−0.000	(0.010)
Bank 3	0.000	(0.010)
Bank 4	−0.071	(0.011)
Local demand	0.026	(0.003)
Own branches	−0.094	(0.008)
Rival branches	−0.055	(0.008)
Crisis	−0.529	(0.090)
Crisis × Local demand	−0.026	(0.018)

Local demand is measured using GDP-intercalibrated night-time luminosity in a 20km radius around the market centroid.

TABLE 3: Structural Parameter Estimates.

we also show how the total number of branch openings and closings per year predicted by the model compare with the data. In general, the model captures total branch openings and closings well. However, the model predicts the peak of branch closings to occur in 1998, whereas in the data the peak occurs in 2001.

6 Understanding Branching During the Crisis

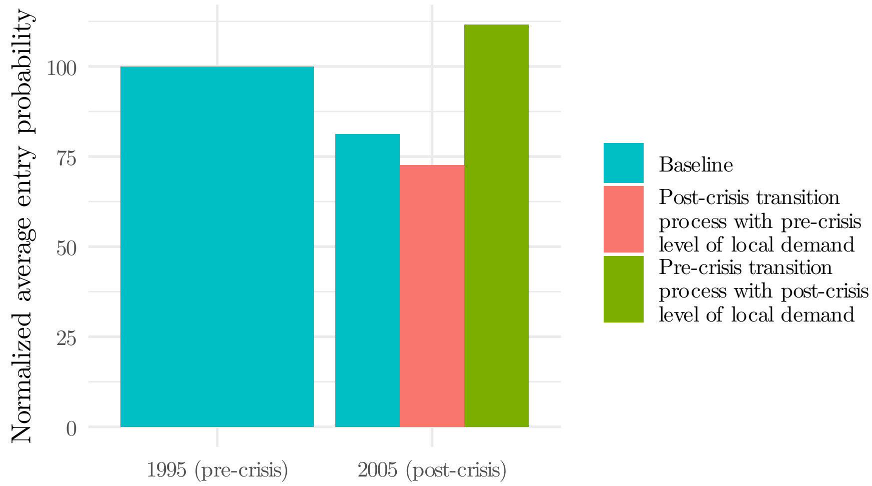
We now use our model to understand how the financial crisis of 1997 affected the banks' branching strategies. We first use the model to understand how the lower growth rates after the crisis slowed the expansion of the branch network. We then simulate the branching decisions that would have occurred in the absence of the crisis to measure the impact of the crisis on financial access. Finally, we simulate the effect of bank branch supports during crisis on improving financial access both during and after the crisis.

6.1 Lower Growth Rates and Branching Strategies

Although GDP returned to its pre-crisis level by 2002, the aggregate number of branches returned to its pre-crisis level only by 2006. Furthermore, there were a number of markets that were served before the crisis but had fewer or no branches even until the end of our sample period.

Part of this slow recovery is the large cost of opening a branch relative to the per-period profits of a branch. Our estimated entry cost is 25.3 times the average annual profits for a branch. Even though a rural branch that closed during the crisis may have been profitable after the crisis was over, the profits may not have been large enough to justify paying the large cost of entry again. But if it was optimal to pay this large entry cost before the crisis, why did banks not reopen them after the crisis was over and GDP had recovered to its pre-crisis level? Many of the branches in the hard-hit locations were opened in the late 1980s and early 1990s when the average annual growth rate in GDP was approximately 9%. Following the crisis, the average growth rate was only 4-5%. Because the banks are forward-looking, the lower growth rate in the post-crisis period made it less attractive to open branches in many locations. Thus, our dynamic model provides an explanation for this lower rate of entry after the crisis.

According to our estimated model, the average probability of opening a branch was 24.6% smaller in 2005 compared to 1995. Part of this change is driven by the change in the transition process of local demand, but it is also affected by differences in the level of local demand and the number of active branches through cannibalization and competition. When branches closed in many markets during the crisis, the reduction in financial access in these locations also lowered the growth rate of local demand, making it even less



The blue bars show the normalized average entry probabilities in 1995 and 2005 in markets of type 1-3 with no active branches at the average level of local demand in those markets in those years. Probabilities are normalized relative to 1995. The red bar shows the average entry probabilities in 2005 at the level of local demand in 1995. The green bar shows the average entry probabilities in 2005 in the counterfactual scenario where the transition process of local demand continued according to the pre-crisis process.

Figure 10: Changes in the average entry probabilities before and after the crisis.

attractive for banks to open branches in these locations in the future.

In order to isolate the effects of cannibalization, competition and the effect of branches on growth, we focus on markets without any active branches. We also focus on the markets more vulnerable at becoming unbanked and focus on market types 1-3.[13] In Figure 10 we show the average entry probabilities of banks in markets without active branches in 1995 and 2005 at the average level of local demand in those markets in those years. We normalize probabilities relative to 1995. Our model shows a decrease in the average entry probability of 18.7% between 2005 and 1995 in these markets, despite the fact that local demand in 2005 was on average 14.9% higher. This is shown by the blue bars in Figure 10. If local demand was at its 1995 level in 2005, the average

[13]The results that follow also hold when we look at other groupings of market types, such as 1-2, or 1-4. When looking at all market types together the qualitative results are the same but with smaller changes.

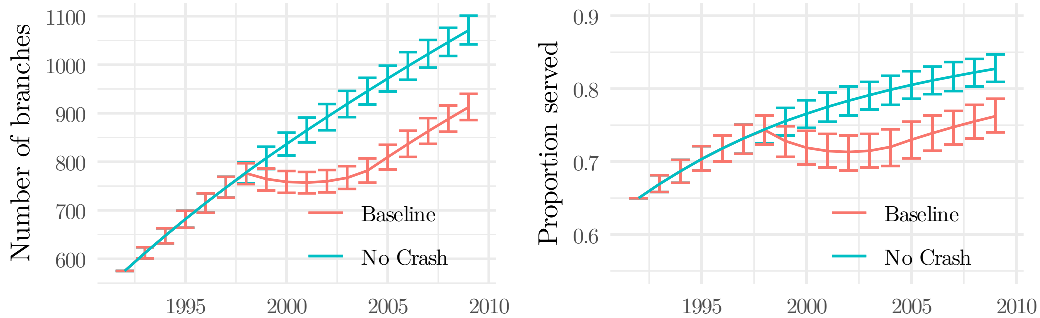
entry probability would have been 27.4% lower. This is shown by the red bar in Figure 10. To understand the effect of the change in the local demand transition process on branching decisions, we run a counterfactual experiment where the transition process for local demand continues according to the pre-crisis process into the post-crisis period. We then solve for the equilibrium strategies of the banks. In this case, the entry probability would have been 11.6% larger in 2005 compared to 1995. This is shown by the green bar in Figure 10. This increase relative to 1995 is driven by the larger level of local demand in later years. Therefore the change in the growth rate of local demand after the crisis made it less attractive for banks to open branches, even though the level of local demand had recovered to its pre-crisis level.[14]

6.2 The Effect of the Financial Crisis

We now use the model to estimate the effect of the crisis on financial access. We run a counterfactual experiment where we simulate the expansion of the bank branch network under the scenario where the financial crisis of 1997 does not occur. We set the crash indicator ζ_t equal to zero and use the pre-crisis process of local demand for all time periods. In this counterfactual, the crash does not occur and firms do not place a positive probability of it occurring in the future. We then solve for the equilibrium strategies of the banks.

Figure 11 shows the results from 1,000 simulations according to these equilibrium strategies. Figure 11a shows the average number of branches on aggregate from our simulations, together with error bands that contain 95% of the simulations. The baseline model predictions are also shown for comparison purposes. We can see that the number of active branches continued according to the pre-crash trend in the absence of the crisis. By 2007, ten years after the crisis, there were 18.5% more branches. In Figure A.8 in the Online Appendix we also plot the difference in these outcomes over time with error bars for the

[14] An alternative explanation for the change in entry rates could be a change in the reserve requirement ratio. However, the reserve requirement ratio fell from 7% to 6% in 1997 and remained there until 2016. Therefore we do not believe these requirements caused the entry patterns to change.



(A) Number of active branches. (B) Proportion of served markets.

FIGURE 11: Branch network expansion under no crash versus baseline.

differences.

We are interested not only in the total number of branches, but also the proportion of markets served by at least one branch, as markets without any branches have poorer access to credit. For each of our simulated network expansion paths, we also calculate the proportion of markets that had at least one branch from the banks in our model. We do this under the no-crash counterfactual and under the estimated model parameters. This is shown in Figure 11b, together with error bars that contain 95% of our simulations. We can see that in the years following a crash, the number of markets served fell and did not recover until the end of our sample period. However, under the no-crash counterfactual, the proportion of served markets continued according to the pre-crash trend, with 9.3% more markets served by 2007 compared to the baseline scenario.

Markets which saw their branches close may still have access to branches in nearby markets. We calculate the distance to the nearest branch in the baseline case and this counterfactual.[15] Figure 12 shows the change in distance to the nearest branch on average from our simulations. Many locations saw an increase in distance with some locations seeing an increase of up to 20km. Ji et al. (forthcoming) estimate a regression model using Thai data ex-

[15] Although we exclude a subset of markets in estimation, we use the full set of 520 markets to perform this calculation.

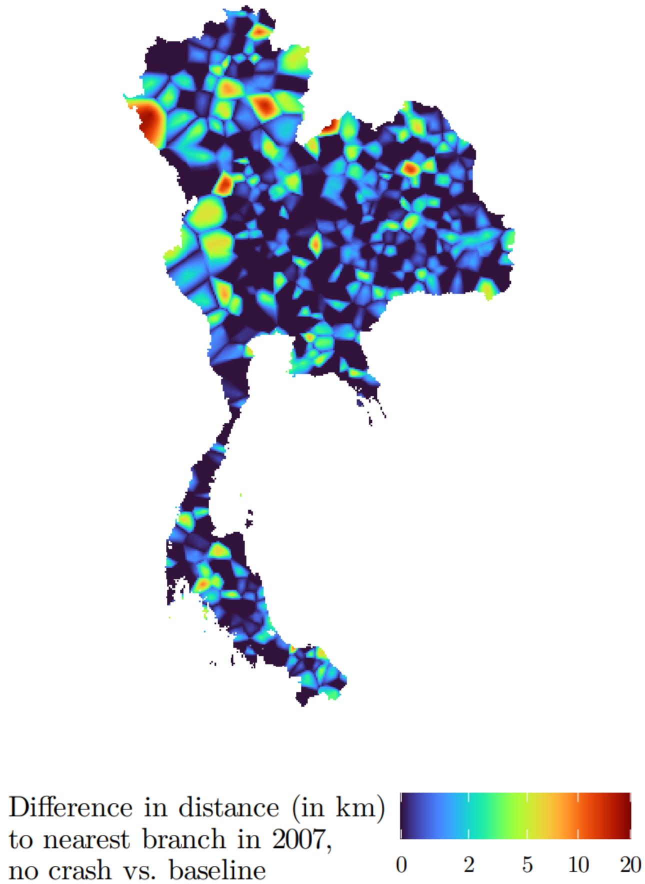


FIGURE 12: Effect of the crisis on distance to nearest branch.

plaining the access to loans by the distance to the nearest branch. Using their estimated effect with our predicted change in distance of 31.2%, village access to commercial loans would have been 8.0 percentage points higher in the absence of the crisis, over a baseline percentage with access of 43.6% in 1996.[16] If we focus on the markets that were more severely affected (those which saw a long-term reduction in the number of branches), the average distance would have fallen by 51.6% and financial access would have been 14.5 percentage

[16]Access to commercial loans in Ji et al. (forthcoming) is a dummy variable which equals one if the village head stated that households in the village had obtained loans from a commercial bank.

points higher.

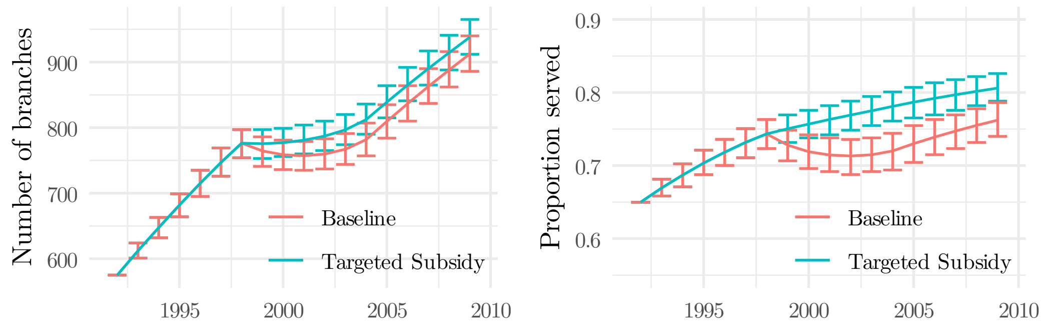
We also decompose the effects of the crisis indicator, the fall in local demand, the slowdown of local demand on branching in Online Appendix A.3. We find that the crisis indicator explains 75.7% of the drop in branches.

6.3 Targeted Branch Supports

We now consider the effect of bank branch supports on maintaining the branch network during the crisis. During the crisis, banks faced liquidity issues and closed branches in many locations. After the crisis was over, banks often never reopened the closed branches, even though those branches may have had positive profits after the crisis was over. This is because our estimated entry cost is 25.3 times the average annual profits for a branch, and the growth rate of local demand fell in the post-crisis period. If branches in vulnerable markets were supported with subsidies for the duration of the crisis period, markets that saw all their branches close may instead continue to retain those branches throughout and after the crisis period. This improved financial access can increase local growth through further investment, and can also have other positive externalities such as enabling consumption smoothing.

For this counterfactual, we consider a targeted branch support subsidy for vulnerable markets. For the purpose of this counterfactual, we define a vulnerable market as a market with only one branch. For branches in these markets we consider a subsidy equal to $-\left(\theta^{crisis} + \theta^{crisis,z} z_{mt}\right)$ for the years where the crisis indicator, ζ_t, equals one. Although this subsidy does not compensate branches entirely for the decrease in local demand and subsequent slowdown in growth, it covers the majority of losses induced by the crisis.[17] We assume the same process for local demand as in the baseline case for this counterfactual. Because the crisis indicator also captures the effect of lower liquidity on the banks' branching strategies, this counterfactual can also be interpreted as easing the liquidity issues faced by the banks.

[17]Based on the decomposition of the crisis shown in Online Appendix A.3 in the Online Appendix, the crisis indicator alone accounts for 75.7% for decrease in branches from the crisis.



(A) Number of active branches. (B) Proportion of served markets.

FIGURE 13: Branch network expansion under bank branch support subsidy versus baseline.

The results are shown in Figure 13, presented in the same format as Figure 11 for ease of comparison. Figure 13a shows that although the total number of branches did not continue according to its pre-crash trend, the total size of the branch network did not decrease following the crisis. Ten years following the crisis, the total number of branches is approximately 3.2% higher compared to the baseline scenario. Similarly, Figure 13b shows that the subsidy prevented the proportion of served markets from decreasing, but with fewer markets served compared to the no-crash scenario. By 2007, the proportion of served markets was 6.6% higher compared to the baseline. This is large relative to the 9.3% increase in the percentage of served markets that would have occured if the crash did not occur at all. In Figure A.9 in the Online Appendix we also plot the difference in these outcomes over time with error bars for the differences, where we observe a significant increase in the number of branches and proportion of served markets under the targeted subsidy.

Based on our simulations, between 179 and 196 branches receive the subsidy each year. Using the estimated dollar value of the parameter estimates, the cost of providing these subsidies is between US$128-148m per year on aggregate. This is approximately US$738,000 per subsidy-receiving branch, which is 34% higher than the annual profits of the average branch just before the crisis (US$548,983).

7 Robustness

In this section we show that the results from our main counterfactual simulations are not sensitive to our modeling assumptions.

We first reestimate our model using a 15km radius to construct market clusters, instead of our baseline threshold of 10km. Figure A.10 in the Online Appendix shows the differences between the clustering approaches for the branch locations in Southern Thailand. We also proportionally adjust the radius in which we calculate local demand. In Table A.2, we show the structural estimates under each approach. In Figure A.11 we show the results from the no financial crisis counterfactual simulation with these estimates. Both the structural parameter estimates and estimated effects of the financial crisis are very similar under each radius.

We also compare our model's predictions under an alternative assumption of the banks' beliefs regarding the evolution of the crisis indicator, ζ_t. In our baseline model, banks learn the true process of ζ_t once the crisis arrives. In this robustness check, instead of assuming that banks learn the true process of ζ_t when the crisis arrives, we assume that banks learn the true process only after the crisis is over. During the crisis (between 1998 and 2004), banks believe that $\zeta_t = 1$ in all future time periods. Once the crisis is over, banks learn the true process of ζ_t and believe $\zeta_t = 0$ in all future time periods. We estimate the parameters of the model according to this assumption and re-run the no crisis counterfactual. The structural estimates are shown in Table A.3 and the counterfactual simulation is shown in Figure A.12. Our estimate of θ^{crisis} is close to zero in this specification, and the interaction of the crisis with local demand is smaller. However, the estimated effect of the crisis on financial access is very similar to our baseline specification.

In our baseline model specification, we allow banks to internalize the effect of their entry decisions on the transition process of local demand, as we find the number of active branches has a positive impact on local growth. We perform a robustness check where we instead assume that banks take the growth rate of local demand as given and do not internalize the effect of their actions on growth. We do this by reestimating the regression model in equation (10) that generates the transition process but omitting the number of active branches as a regressor. The structural estimates using this transition process are shown in Table A.4. Although not statistically different, the coefficients on own and rival branches are slightly smaller in magnitude in this specification. In our baseline specification, markets with more branches grow faster, which partially offsets the competitive effect of branches. Because this effect is not taken into account when banks do not internalize the effect of branching on growth, these coefficients become slightly smaller in magnitude. We also repeat the no-crash counterfactual using this method. This is shown in Figure A.13. We again find that the effect of the crisis in the counterfactual simulation to be very similar to our baseline specification.

Although the effect of local branches on local GDP growth has been previously documented (Fulford, 2015; Nguyen, 2019; Young, 2021), our estimated effect of branches on our local demand transitions may be upward biased if there are unobservables that affect growth that are positively correlated with the number of branches beyond the market effect (θ_k) that we include. We test the sensitivity of our results to possible upward bias in the estimated coefficient on the total number of branches in Table A.1 by setting the coefficient to half its size and reestimating our structural parameters. The estimates are shown in Table A.5. The parameter estimates and results from the no-crisis counterfactual are again very similar to our baseline results.

Some market observers believe these banks coordinate their actions in certain ways (Lauridsen, 1998). We also check if our results are robust to the possibility that the banks coordinate their branching decisions. We do this by comparing our model's predictions under the alternative assumption that the four banks behave as a cartel. In this specification, we assume a single bank makes all branching decisions to maximize the sum of all banks' payoffs. Instead of having two separate competition parameters for own and rival branches, we estimate a single parameter. The estimates are shown in Table A.6 together with our baseline estimates. The estimated entry cost is smaller compared to the baseline specification, and the competitive effect of the cartel's own branches is in between the effect of own and rival branches in the baseline specification. The effects of the crisis under this modeling assumption are shown in Figure A.15. We obtain similar results for the percentage of served markets and financial access, but due to the lack of competition, slightly fewer branches open in the absence of the crisis.

Finally, we also tested for multiple equilibria in our baseline model by solving the model at different initial guesses of the banks' strategies. In each case, the converged strategies were numerically identical.

8 Conclusion

In this paper, we argue that the effect of financial crises on bank branch location choices provides an unexplored channel by which crises affect access to credit. Because opening new branches entails a large up-front investment, markets that see branches close during the crisis may go unbanked for many years after the overall economy recovers. We study this issue in the context of the 1997 Thai financial crisis by estimating a dynamic structural model of banks' branching strategies. In the model, we allow for complementarity in payoffs for branches in the same market, as well as competitive effects between rival banks. Our dynamic model is able to match aggregate moments in our data, and is able to rationalize why banks failed to reopen closed branches after the economy recovered through the lower growth rates of GDP after the crisis.

Using this model, we predict the evolution of bank branch locations under the counterfactual scenarios of no financial crisis in 1997 and with bank branch support subsidies. We find that the financial crisis had large impacts on the total number of branches and the proportion of markets served by at least one branch. We find that there would have been 18.5% more branches and 9.3% more markets with at least one branch after ten years had the crisis not occurred. We calculate that access to loans tens years later would have increased by 8.0 percentage points in the absence of the crisis. Subsidies for branches in markets that are at risk of becoming unbanked could also have prevented the proportion of markets served by a branch from falling below pre-crisis levels.

References

Agarwal, S. and R. Hauswald (2010): "Distance and Private Information in Lending," *The Review of Financial Studies*, 23, 2757–2788.

Aguirregabiria, V., R. Clark, and H. Wang (2016): "Diversification of Geographic Risk in Retail Bank Networks: Evidence from Bank Expansion after the Riegle-Neal Act," *The RAND Journal of Economics*, 47, 529–572.

Aguirregabiria, V. and J. Jeon (2020): "Firms' Beliefs and Learning: Models, Identification, and Empirical Evidence," *Review of Industrial Organization*, 56, 203–235.

Alem, M. and R. M. Townsend (2014): "An Evaluation of Financial Institutions: Impact on Consumption and Investment Using Panel Data and the Theory of Risk-bearing," *Journal of Econometrics*, 183, 91–103.

Allen, F., E. Carletti, R. Cull, J. Q. Qian, L. Senbet, and P. Valenzuela (2021): "Improving Access to Banking: Evidence from Kenya," *Review of Finance*, 25, 403–447.

Assuncao, J., S. Mityakov, and R. M. Townsend (2020): "Public Ownership and Anti-Preemption," Working Paper.

Attanasio, O., K. Larkin, M. O. Ravn, and M. Padula (2022): "(S)Cars and the Great Recession," *Econometrica*, 90, 2319–2356.

Augereau, A., S. Greenstein, and M. Rysman (2006): "Coordination versus differentiation in a standards war: 56k modems," *The RAND Journal of Economics*, 37, 887–909.

Banerjee, A., E. Duflo, R. Glennerster, and C. Kinnan (2015a): "The Miracle of Microfinance? Evidence from a Randomized Evaluation," *American Economic Journal: Applied Economics*, 7, 22–53.

Banerjee, A., D. Karlan, and J. Zinman (2015b): "Six Randomized Evaluations of Microcredit: Introduction and Further Steps," *American Economic Journal: Applied Economics*, 7, 1–21.

Beck, T., A. Demirgüç-Kunt, and V. Maksimovic (2004): "Bank Competition and Access to Finance: International Evidence," *Journal of Money, Credit and Banking*, 627–648.

Bernanke, B. S. (1983): "Nonmonetary Effects of the Financial Crisis in the Propagation of the Great Depression," *American Economic Review*, 73, 257–276.

Collard-Wexler, A. (2013): "Demand Fluctuations in the Ready-Mix Concrete Industry," *Econometrica*, 81, 1003–1037.

Crawford, G. S., N. Pavanini, and F. Schivardi (2018): "Asymmetric Information and Imperfect Competition in Lending Markets," *American Economic Review*, 108, 1659–1701.

Degryse, H. and S. Ongena (2005): "Distance, Lending Relationships, and Competition," *The Journal of Finance*, 60, 231–266.

Dell'Ariccia, G., E. Detragiache, and R. Rajan (2008): "The Real Effect of Banking Crises," *Journal of Financial Intermediation*, 17, 89–112.

Dunne, T., S. D. Klimek, M. J. Roberts, and D. Y. Xu (2013): "Entry, Exit, and the Determinants of Market Structure," *The RAND Journal of Economics*, 44, 462–487.

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

Fulford, S. L. (2015): "How Important are Banks for Development? National Banks in the United States, 1870–1900," *Review of Economics and Statistics*, 97, 921–938.

Henderson, V., A. Storeygard, and D. N. Weil (2012): "Measuring Economic Growth from Outer Space," *American Economic Review*, 102, 994–1028.

Hidalgo, J. and M. Sovinsky (2022): "Subsidies, Speed and Switching? Impacts of an Internet Subsidy in Colombia," *CEPR DP17663*.

Ho, K. and J. Ishii (2011): "Location and Competition in Retail Banking," *International Journal of Industrial Organization*, 29, 537–546.

Holmes, T. J. (2011): "The Diffusion of Wal-Mart and Economies of Density," *Econometrica*, 79, 253–302.

Huckfeldt, C. (2022): "Understanding the Scarring Effect of Recessions," *American Economic Review*, 112, 1273–1310.

Igami, M. (2017): "Estimating the Innovator's Dilemma: Structural Analysis of Creative Destruction in the Hard Disk Drive Industry, 1981–1998," *Journal of Political Economy*, 125, 798–847.

Igami, M. and N. Yang (2016): "Unobserved Heterogeneity in Dynamic Games: Cannibalization and Preemptive Entry of Hamburger Chains in Canada," *Quantitative Economics*, 7, 483–521.

Jayaratne, J. and P. E. Strahan (1996): "The Finance-Growth Nexus: Evidence from Bank Branch Deregulation," *The Quarterly Journal of Economics*, 111, 639–670.

Jeon, J. (2022): "Learning and investment under demand uncertainty in container shipping," *The RAND Journal of Economics*, 53, 226–259.

Ji, Y., S. Teng, and R. Townsend (forthcoming): "Dynamic Bank Expansion: Spatial Growth, Financial Access, and Inequality," *Journal of Political Economy*.

Kaboski, J. P. and R. M. Townsend (2011): "A Structural Evaluation of a Large-Scale Quasi-Experimental Microfinance Initiative," *Econometrica*, 79, 1357–1406.

Lauridsen, L. S. (1998): "The Financial Crisis in Thailand: Causes, Conduct and Consequences?" *World Development*, 26, 1575–1591.

Lin, H. (2015): "Quality Choice and Market Structure: A Dynamic Analysis of Nursing Home Oligopolies," *International Economic Review*, 56, 1261–1290.

Love, I. and M. S. Martínez Pería (2015): "How Bank Competition Affects Firms' Access to Finance," *The World Bank Economic Review*, 29, 413–448.

Marín, A. G. and R. Schwabe (2019): "Bank Competition and Financial Inclusion: Evidence from Mexico," *Review of Industrial Organization*, 55, 257–285.

Michalopoulos, S. and E. Papaioannou (2013): "Pre-Colonial Ethnic Institutions and Contemporary African Development," *Econometrica*, 81, 113–152.

Nguyen, H.-L. Q. (2019): "Are Credit Markets Still Local? Evidence from Bank Branch Closings," *American Economic Journal: Applied Economics*, 11, 1–32.

Petersen, M. A. and R. G. Rajan (2002): "Does Distance Still Matter? The Information Revolution in Small Business Lending," *The Journal of Finance*, 57, 2533–2570.

Ryan, N. (2021): "The Competitive Effects of Transmission Infrastructure in the Indian Electricity Market," *American Economic Journal: Microeconomics*, 13, 202–42.

Ryan, S. P. (2012): "The Costs of Environmental Regulation in a Concentrated Industry," *Econometrica*, 80, 1019–1061.

Seim, K. (2006): "An Empirical Model of Firm Entry with Endogenous Product-Type Choices," *The RAND Journal of Economics*, 37, 619–640.

Vitali, A. (2022): "Consumer Search and Firm Location: Theory and Evidence from the Garment Sector in Uganda," Working Paper.

Walsh, C. (2020): "Social Impacts of New Radio Markets in Ghana: A Dynamic Structural Analysis," Working Paper.

Wu, J., S. He, J. Peng, W. Li, and X. Zhong (2013): "Intercalibration of DMSP-OLS Night-time Light Data by the Invariant Region Method," *International Journal of Remote Sensing*, 34, 7356–7368.

Young, N. (2021): "Banking and Growth: Evidence from a Regression Discontinuity Analysis," Working Paper.

Zheng, F. (2016): "Spatial Competition and Preemptive Entry in the Discount Retail Industry," *Available at SSRN 2775498.*

Online Appendix to:

Bank Branching Strategies in the 1997 Thai Financial Crisis and Local Access to Credit

by Marc Rysman, Robert M. Townsend, and Christoph Walsh

A.1 Additional Figures and Tables

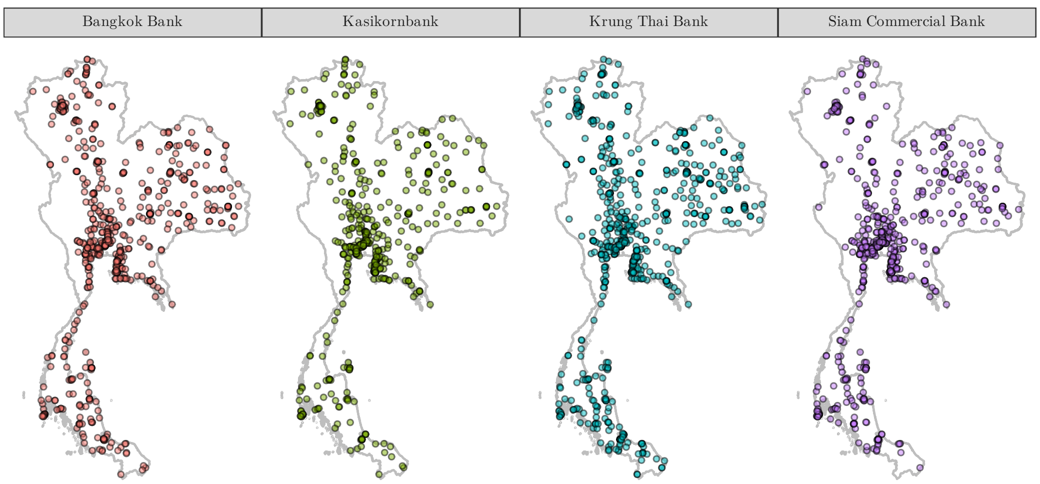


FIGURE A.1: Locations of all branches ever held by each of the four largest banks.

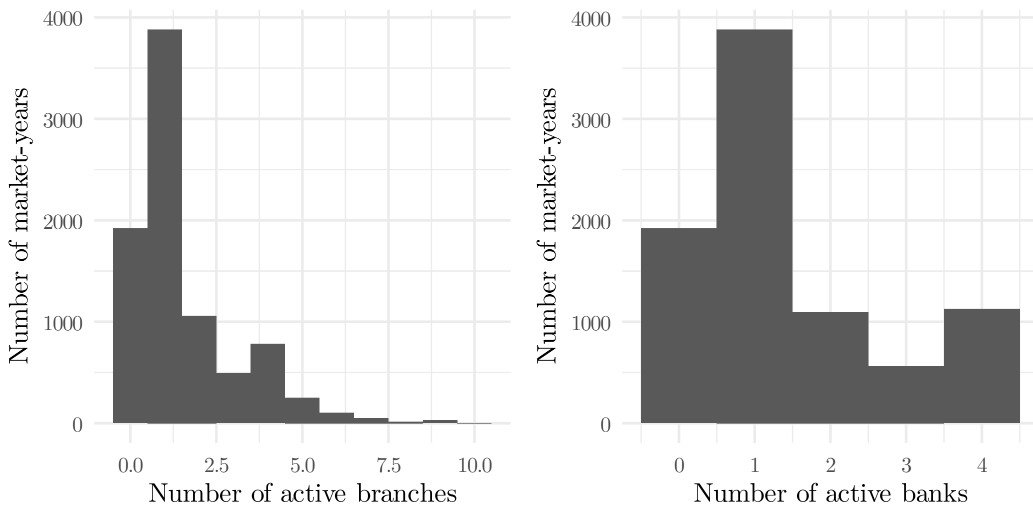
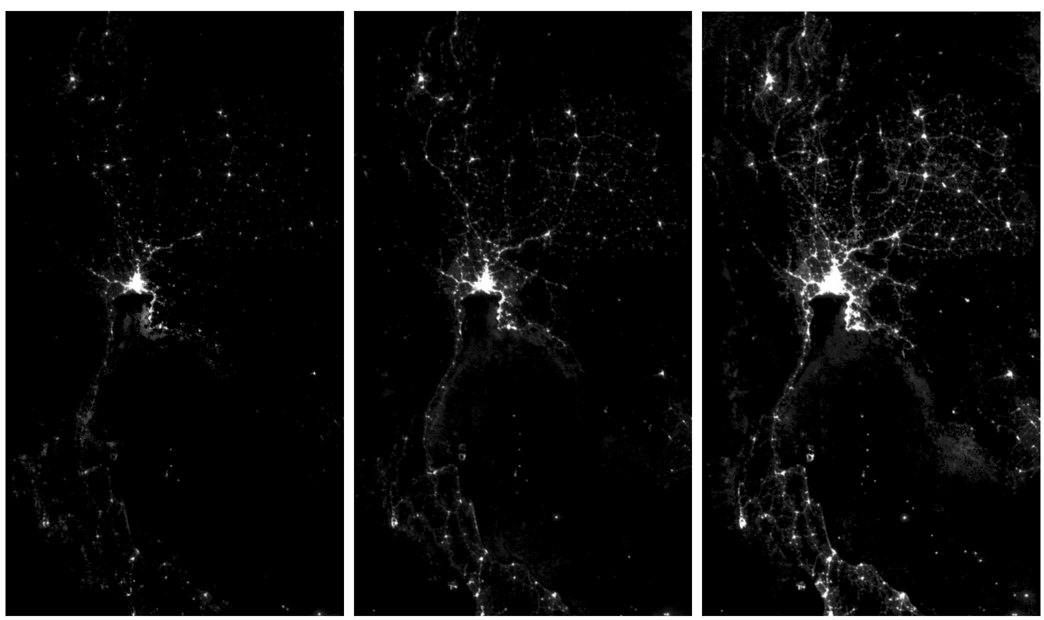


FIGURE A.2: Number of active branches and active banks in market-years used in estimation.



(A) 1992 (B) 2001 (C) 2010

FIGURE A.3: GDP-intercalibrated nighttime luminosity data over time.

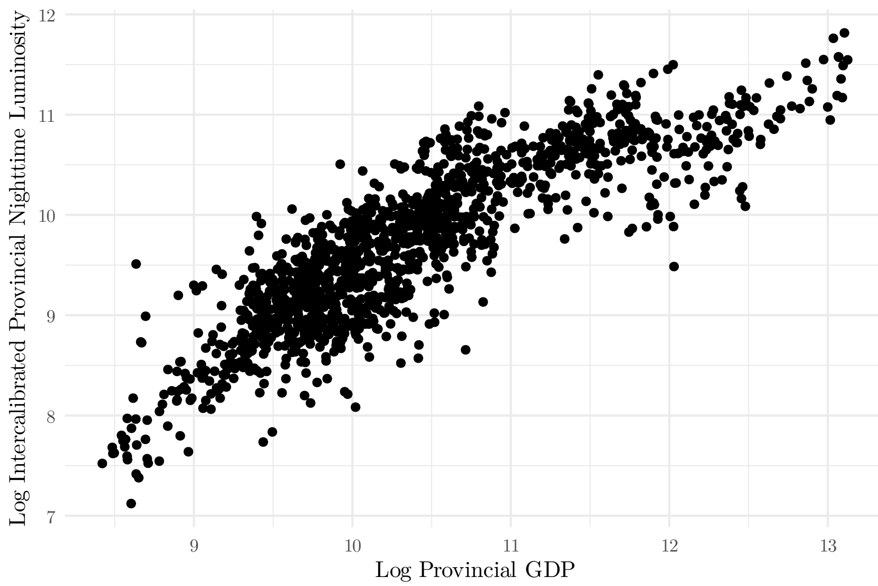
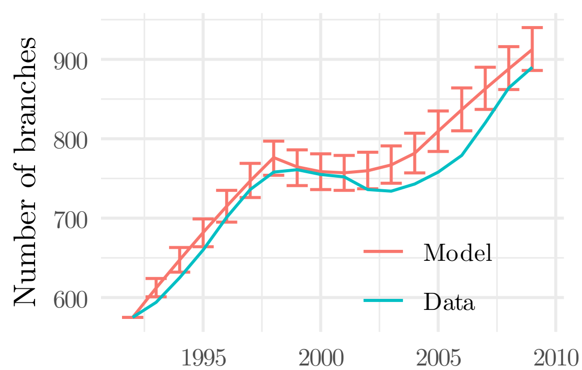


FIGURE A.4: Log provincial GDP versus log provincial nighttime luminosity.



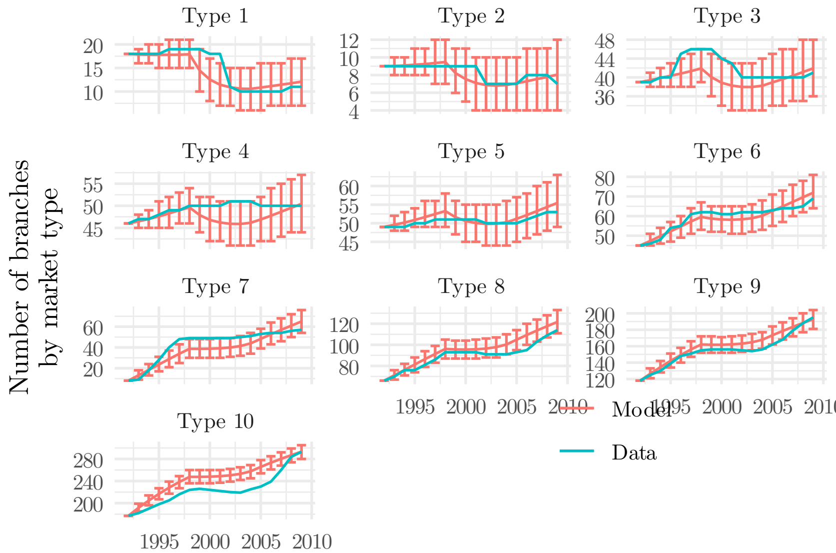
Error bands contain 95% of simulated paths from 1,000 simulations.

FIGURE A.5: Number of branches by year predicted by model versus data

Dependent variable: Change in local demand		
Market type 1 ($\widehat{\eta}_1$)	0.321	(0.057)
Market type 2 ($\widehat{\eta}_2$)	0.219	(0.057)
Market type 3 ($\widehat{\eta}_3$)	0.267	(0.058)
Market type 4 ($\widehat{\eta}_4$)	0.223	(0.058)
Market type 5 ($\widehat{\eta}_5$)	0.245	(0.058)
Market type 6 ($\widehat{\eta}_6$)	0.261	(0.059)
Market type 7 ($\widehat{\eta}_7$)	0.214	(0.057)
Market type 8 ($\widehat{\eta}_8$)	0.278	(0.061)
Market type 9 ($\widehat{\eta}_9$)	0.205	(0.068)
Market type 10 ($\widehat{\eta}_1 0$)	0.176	(0.079)
Market type 1 $\times Post_t$ ($\widehat{\eta}_1^{post}$)	-0.113	(0.070)
Market type 2 $\times Post_t$ ($\widehat{\eta}_2^{post}$)	-0.224	(0.070)
Market type 3 $\times Post_t$ ($\widehat{\eta}_3^{post}$)	-0.170	(0.070)
Market type 4 $\times Post_t$ ($\widehat{\eta}_4^{post}$)	-0.199	(0.070)
Market type 5 $\times Post_t$ ($\widehat{\eta}_5^{post}$)	-0.318	(0.070)
Market type 6 $\times Post_t$ ($\widehat{\eta}_6^{post}$)	-0.235	(0.071)
Market type 7 $\times Post_t$ ($\widehat{\eta}_7^{post}$)	-0.229	(0.070)
Market type 8 $\times Post_t$ ($\widehat{\eta}_8^{post}$)	-0.339	(0.071)
Market type 9 $\times Post_t$ ($\widehat{\eta}_9^{post}$)	-0.152	(0.070)
Market type 10 $\times Post_t$ ($\widehat{\eta}_1^{post} 0$)	-0.299	(0.071)
Total number of branches ($\widehat{\alpha}$)	0.044	(0.014)
1997 dummy ($\widehat{\delta}_{96}$)	-0.412	(0.048)
1998 dummy ($\widehat{\delta}_{97}$)	-0.464	(0.048)

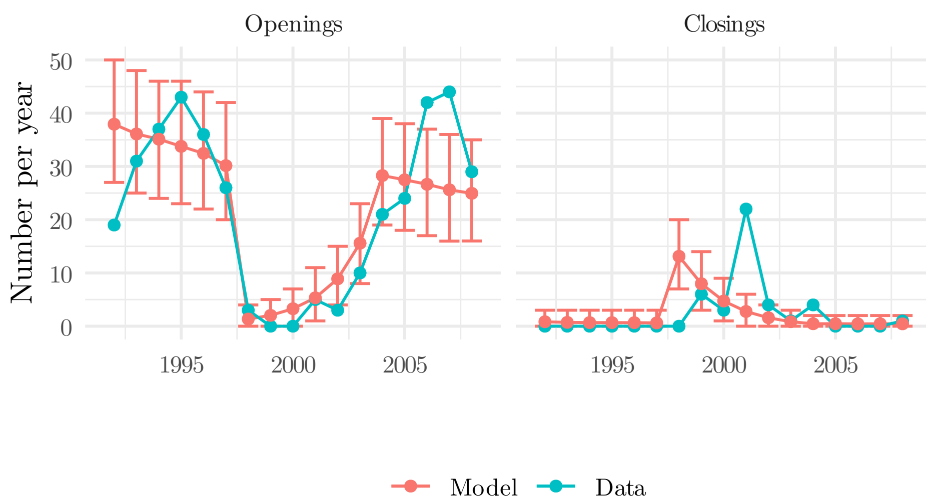
Estimates from a linear regression. Standard errors in parentheses. Local demand is measured using GDP-intercalibrated nighttime luminosity in a 20km radius around the market centroid.

TABLE A.1: Regression model generating local demand transitions.



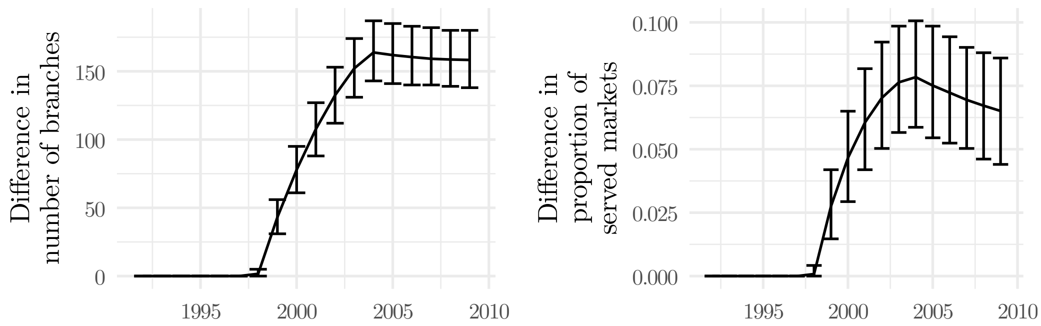
Error bands contain 95% of simulated paths from 1,000 simulations.

Figure A.6: Predicted number of active branches versus data by market type.



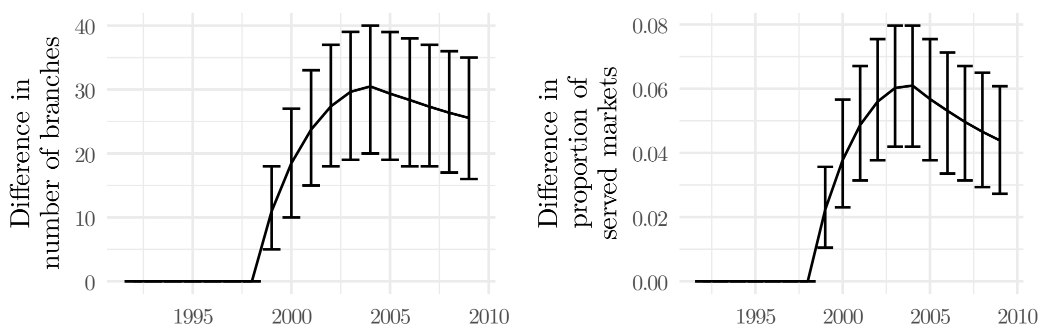
Error bands contain 95% of simulated paths from 1,000 simulations.

Figure A.7: Number of openings and closings predicted by model versus data



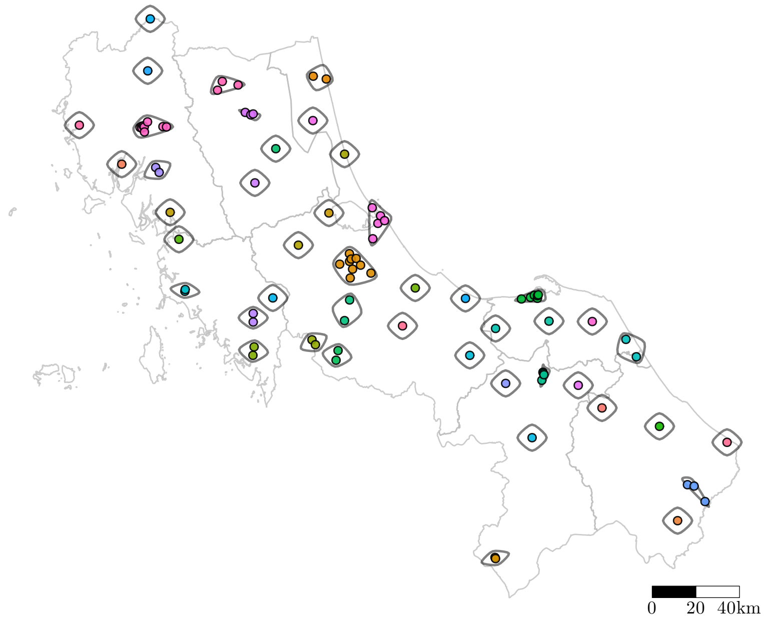
(A) Number of active branches. (B) Proportion of served markets.

Figure A.8: Difference in branch network expansion outcomes: no crash versus baseline.

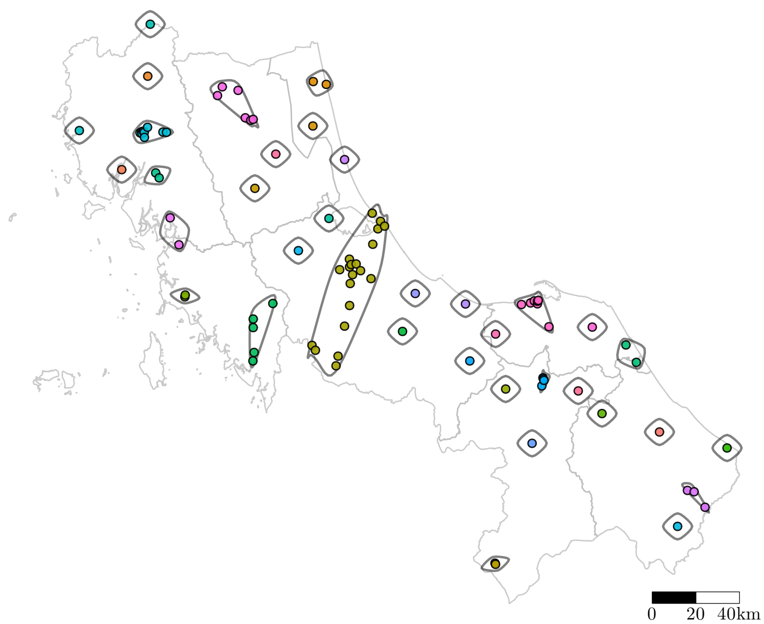


(A) Number of active branches. (B) Proportion of served markets.

Figure A.9: Difference in branch network expansion outcomes: targeted subsidy versus baseline.



(A) 10km threshold



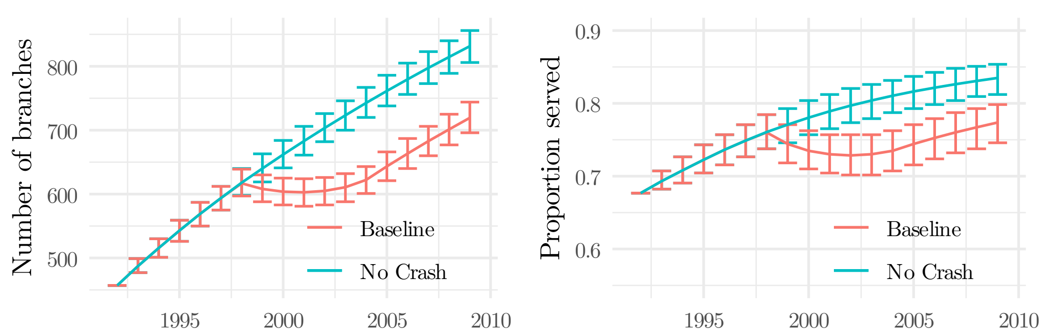
(B) 15km threshold

FIGURE A.10: Clustering locations under a 10km and 15km radius in Southern Thailand.

	Distance	*Threshold*
	10km	15km
Entry cost	11.712	11.773
	(0.292)	(0.336)
Local demand	0.026	0.016
	(0.003)	(0.003)
Own branches	−0.094	−0.088
	(0.008)	(0.008)
Rival branches	−0.055	−0.056
	(0.008)	(0.008)
Crisis	−0.529	−0.501
	(0.090)	(0.103)
Crisis × Local demand	−0.026	−0.021
	(0.018)	(0.014)
Market type fixed effects	Yes	Yes
Bank fixed effects	Yes	Yes
No crash counterfactual: 10 years after crisis compared to baseline		
Percentage change in number of branches	18.45	16.79
Percentage change in markets served	9.29	8.70
Percentage change in average distance to nearest branch	−31.16	−30.09
Percentage point change in financial access	8.03	7.70

Standard errors in parentheses.

TABLE A.2: Structural parameter estimates under a 15km distance thresholds to construct markets clusters versus 10km.

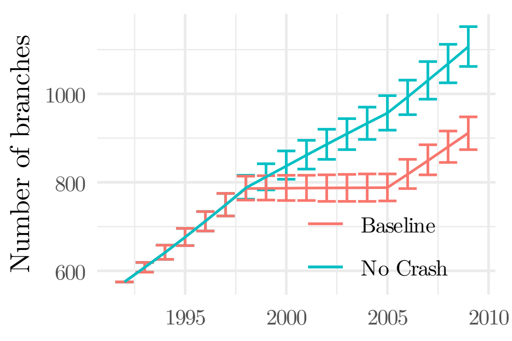


(A) Number of active branches. (B) Proportion of served markets.

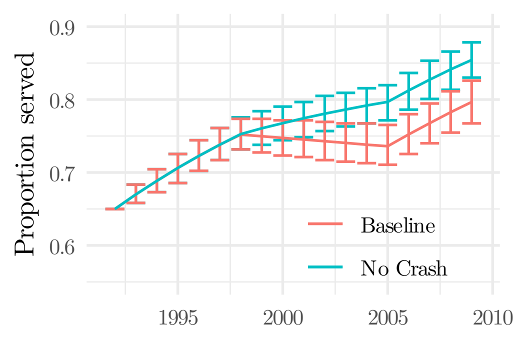
FIGURE A.11: Branch network expansion under no crash versus baseline using a 15km distance threshold to construct markets.

	Baseline specification	Banks believe crash lasts forever
Entry cost	11.712	10.889
	(0.292)	(0.222)
Local demand	0.026	0.015
	(0.003)	(0.002)
Own branches	−0.094	−0.015
	(0.008)	(0.004)
Rival branches	−0.055	−0.000
	(0.008)	(0.000)
Crisis	−0.529	−0.001
	(0.090)	(0.029)
Crisis × Local demand	−0.026	−0.017
	(0.018)	(0.005)
Market type fixed effects	Yes	Yes
Bank fixed effects	Yes	Yes
No crash counterfactual: 10 years after crisis compared to baseline		
Percentage change in number of branches	18.45	21.36
Percentage change in markets served	9.29	7.77
Percentage change in average distance	−31.16	−27.86
Percentage point change in financial access	8.03	7.02

TABLE A.3: Structural estimates assuming banks believe the crisis will last forever.



(A) Number of active branches.

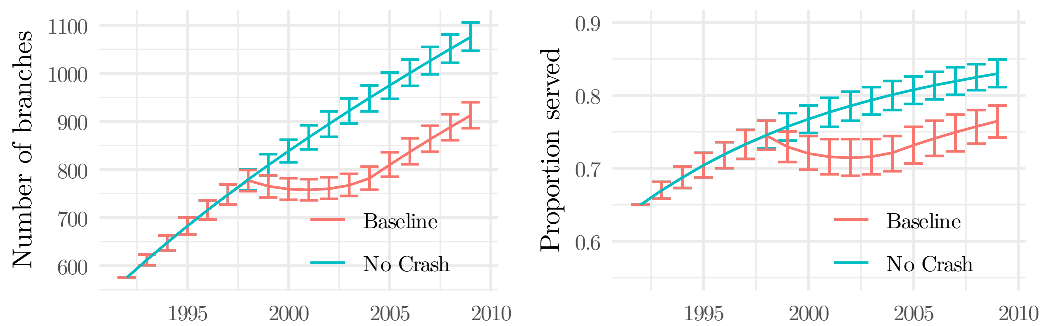


(B) Proportion of served markets.

FIGURE A.12: Branch network expansion under no crash versus baseline under the assumption that banks believe the crisis will last forever.

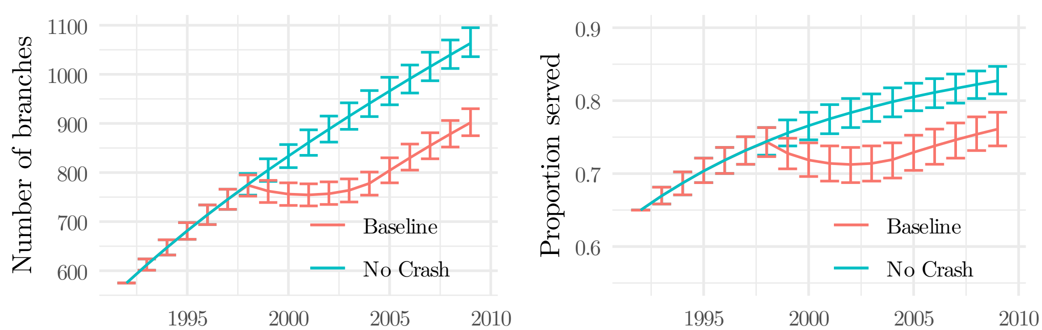
	Banks do internalize effect on growth	Banks do not internalize effect on growth
Entry cost	11.712	11.710
	(0.292)	(0.291)
Local demand	0.026	0.026
	(0.003)	(0.003)
Own branches	−0.094	−0.091
	(0.008)	(0.007)
Rival branches	−0.055	−0.052
	(0.008)	(0.008)
Crisis	−0.529	−0.517
	(0.090)	(0.088)
Crisis × Local demand	−0.026	−0.029
	(0.018)	(0.017)
Market type fixed effects	Yes	Yes
Bank fixed effects	Yes	Yes
No crash counterfactual: 10 years after crisis compared to baseline		
Percentage change in number of branches	18.45	18.91
Percentage change in markets served	9.29	9.33
Percentage change in average distance	−31.16	−31.51
Percentage point change in financial access	8.03	8.14

TABLE A.4: Structural estimates when branches do and do not internalize their effect on growth.



(A) Number of active branches. (B) Proportion of served markets.

FIGURE A.13: Branch network expansion under no crash versus baseline under the assumption that banks cannot affect the growth rate of local demand in their branching decisions.

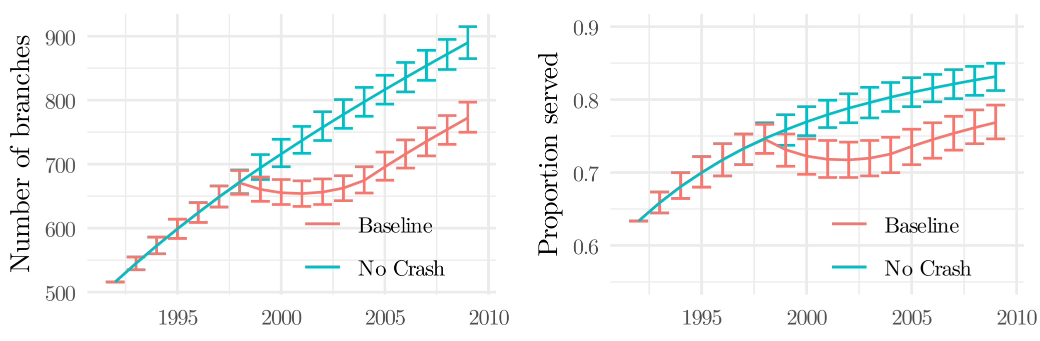


(A) Number of active branches. (B) Proportion of served markets.

FIGURE A.14: Branch network expansion under no crash versus baseline when scaling down $\widehat{\alpha}$ in equation (10) to half its estimated size.

	Baseline specification	Scaled down branch effect on growth
Entry cost	11.712	11.648
	(0.292)	(0.286)
Local demand	0.026	0.027
	(0.003)	(0.003)
Own branches	−0.094	−0.093
	(0.008)	(0.007)
Rival branches	−0.055	−0.054
	(0.008)	(0.008)
Crisis	−0.529	−0.518
	(0.090)	(0.087)
Crisis × Local demand	−0.026	−0.026
	(0.018)	(0.017)
Market type fixed effects	Yes	Yes
Bank fixed effects	Yes	Yes
No crash counterfactual: 10 years after crisis compared to baseline		
Percentage change in number of branches	18.45	18.82
Percentage change in markets served	9.29	9.44
Percentage change in average distance	−31.16	−31.42
Percentage point change in financial access	8.03	8.11

TABLE A.5: Structural estimates when scaling down $\widehat{\alpha}$ in equation (10) to half its estimated size.



(A) Number of active branches. (B) Proportion of served markets.

FIGURE A.15: Branch network expansion under no crash versus baseline under the assumption that banks behave as a cartel.

	Banks compete	Banks coordinate
Entry cost	11.712	9.798
	(0.292)	(0.294)
Local demand	0.026	0.034
	(0.003)	(0.004)
Own branches	−0.094	−0.065
	(0.008)	(0.006)
Rival branches	−0.055	
	(0.008)	
Crisis	−0.529	−0.504
	(0.090)	(0.092)
Crisis × Local demand	−0.026	−0.022
	(0.018)	(0.018)
Market type fixed effects	Yes	Yes
Bank fixed effects	Yes	No
No crash counterfactual: 10 years after crisis compared to baseline		
Percentage change in number of branches	18.45	16.09
Percentage change in markets served	9.29	8.97
Percentage change in average distance	−31.16	−31.01
Percentage point change in financial access	8.03	7.98

Table A.6: Structural estimates when assuming that the banks behave as a cartel.

A.2 Additional Details on Equilibrium Computation

A.2.1 Local Demand Discretization

To solve for the equilibrium choice probabilities, we solve for the value function at a finite number of points. We use 10 different values for local demand with each combination of the number of possible branches for each of the 4 banks (0, 1, 2 or 3). We therefore solve the value function at 2,560 points for each time period and each market type. We denote this discretized state space by $\widetilde{\mathcal{S}}$. To choose these 10 values of local demand, we divide the observed values of local demand into 8 equally-sized bins and take the median value within each bin. In addition, we use 0 (the smallest possible value) and the maximum value observed in the data plus 1. We denote these 10 values by $\widetilde{z}_1 < \widetilde{z}_2 < \cdots < \widetilde{z}_{10}$.

Let $\widehat{z}_{k(m),\tau+1}\left(z_{m\tau}, \sum_{f=1}^{F} n_{fm\tau}\right)$ denote the predicted value from the estimated transition process for local demand in time period $\tau+1$, market type k, with a current value of local demand $z_{m\tau}$ and $\sum_{f=1}^{F} n_{fm\tau}$ active branches. Furthermore, let $\widehat{\sigma}_\nu$ be the standard deviation of residuals from the regression model estimating the local demand transitions. The probability of transitioning from local demand $\widetilde{z}_i$ to $\widetilde{z}_j$ in market type k at time τ given $\sum_{f=1}^{F} n_{fm\tau}$ branches is then given by:

$$\Pr\left(\widetilde{z}_j \middle| \widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}, k(m), \tau\right) =$$
$$\begin{cases} \Phi\left(\frac{-\widehat{z}_{k(m),\tau+1}\left(\widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}\right)}{\widehat{\sigma}_\nu}\right) & \text{if } j=1 \\ 1-\Phi\left(\frac{\widetilde{z}_{10}-\widehat{z}_{k(m),\tau+1}\left(\widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}\right)}{\widehat{\sigma}_\nu}\right) & \text{if } j=10 \\ \Phi\left(\frac{\underline{z}_j-\widehat{z}_{k(m),\tau+1}\left(\widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}\right)}{\widehat{\sigma}_\nu}\right) - \Phi\left(\frac{\underline{z}_{j-1}-\widehat{z}_{k(m),\tau+1}\left(\widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}\right)}{\widehat{\sigma}_\nu}\right) & \text{otherwise} \end{cases} \tag{14}$$

where the $\underline{z}_j$ for $j = 1, \ldots, 8$ are the left cutoff points for each of the 8 bins used to construct the $\widetilde{z}_j$ and $\underline{z}_9 = \widetilde{z}_{10}$.

A.2.2 Updating the Equilibrium Strategy Function

Based on a trial value of the parameter vector $\boldsymbol{\theta}$, we first compute the terminal period value function in each market state (equation (5)). For this we use the discretization of local demand described above and evaluate it at 2,560 points for each time period and market type. To solve for the equilibrium strategy function in period $t = T-1$, we begin with a guess of the action probability of firm f in market m at time t, $p_f^0\left(a_{fmt} = a|\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right)$ for all $a \in \mathcal{A}\left(n_{fmt}\right)$ and each state. For this we use $p_f^0\left(a_{fmt} = a|\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right) = 1$ for $a = 1$ and zero otherwise. That is, the first guess assumes all banks do not open or close any branches in all states.[18] We compute the state transition probabilities $\Pr\left(\boldsymbol{s}_{mt+1} \,|\boldsymbol{s}_{mt}, a\right)$ for any action of the bank $a \in \mathcal{A}\left(n_{fmt}\right)$ using the guess $p_f^0\left(a_{fmt} = a|\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right)$ for the rival banks and the local demand transitions $\Pr\left(\widetilde{z}_j \left| \widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}, k\left(m\right), \tau\right.\right)$ in equation (14).

Based on this iteration of the state transition probabilities, we compute the expected value function in the following period $\mathbb{E}\left[V_f\left(\boldsymbol{s}_{mt+1}, \boldsymbol{\theta}\right)|\boldsymbol{s}_{mt}, a_{fmt} = a\right]$ for bank f for all possible actions $a \in \mathcal{A}\left(n_{fmt}\right)$ from all states $\boldsymbol{s}_t \in \widetilde{\mathcal{S}}$. Using this, we update bank f's action probabilities in each state using equation (8). We update the probabilities for bank $f = 1, \ldots, F$ sequentially.[19] We continue updating these probabilities this way until the maximum absolute change in action probabilities across states from one step to the next is smaller than a pre-specified tolerance level:

$$\max_{\substack{f \in \{1,\ldots,F\},\\ \boldsymbol{s}_{mt} \in \widetilde{\mathcal{S}},\\ a \in \mathcal{A}\left(n_{fmt}\right)}} \left|p_f^j\left(a_{fmt} = a|\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right) - p_f^{j-1}\left(a_{fmt} = a|\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right)\right| < 1 \times 10^{-9} \qquad (15)$$

Once we have solved for the equilibrium strategies in period $T-1$, we compute the ex-ante value function for each firm in each market and each state according

[18] We also tested our procedure by starting with the guess that all banks open a branch in every state and found our algorithm to converge to the same action probabilities.

[19] We assume that banks update their strategies based on the total number of branches they have in the data with the largest banks updating first. We also tested our procedure by reversing the order in which we update banks' strategies and found that it converges to the same entry probabilities.

to equation (7). We then proceed to compute the equilibrium strategies in periods $t = T - 2, \ldots, 1$. This proceeds almost identically to $T - 1$ except that we use the following period's strategy function as the initial guess of the strategies, i.e. $p_f^0 \left(a_{fmt} = a | \boldsymbol{s}_{mt}, \boldsymbol{\theta}\right) = p_f \left(a_{fmt} = a | \boldsymbol{s}_{mt+1}, \boldsymbol{\theta}\right)$ for all a. Because the equilibrium strategies will be the same for all markets of the same market type, we can solve for the equilibrium once for each type instead of each market, which allows for computation in parallel over all 10 market types.

A.3 Decomposition of Crisis Effects

There are three components of our model that change during the crisis that can slow down branch openings and lead to closures. First, the crisis indicator, ζ_t, is activated which lowers profits. Second, there is a fall in local demand brought about by the δ_{96} and δ_{97} terms in equation (10). Third, there is a slowdown in the growth rate of local demand brought about by the $\eta_{k(m)}^{post}$ terms in equation (10). We decompose the effect of each of these terms by running separate counterfactual experiments where we add each of these effects one by one. The results of these experiments are down in Figure A.16. Because we overlay several experiments, we omit error bands to maintain legibility. The red solid lines labelled "No crash" are identical to the no crash counterfactual in Section 6.2. We show both the total number of branches and the proportion of served markets as in Figure 11. The green dashed line labelled "Crash indicator" shows the evolution of the number of branches and proportion of served markets when only the crisis indicator is activated and there is no fall or slowdown in local demand. The blue dotted line labelled "Crash indicator and fall in local demand" shows the results when both the crisis indicator is activated and we allow local demand to fall in 1997 and 1998, but maintain the pre-crisis growth rate after the crisis. Finally, the purple dot-dashed line labelled "Crash indicator, fall in local demand, and growth slowdown" shows the baseline case where the crash occurs.

By 2007, the crisis is estimated to lead to a drop in the number of branches of 15.6%. The crisis indicator alone causes a drop of 11.8%, so the crisis

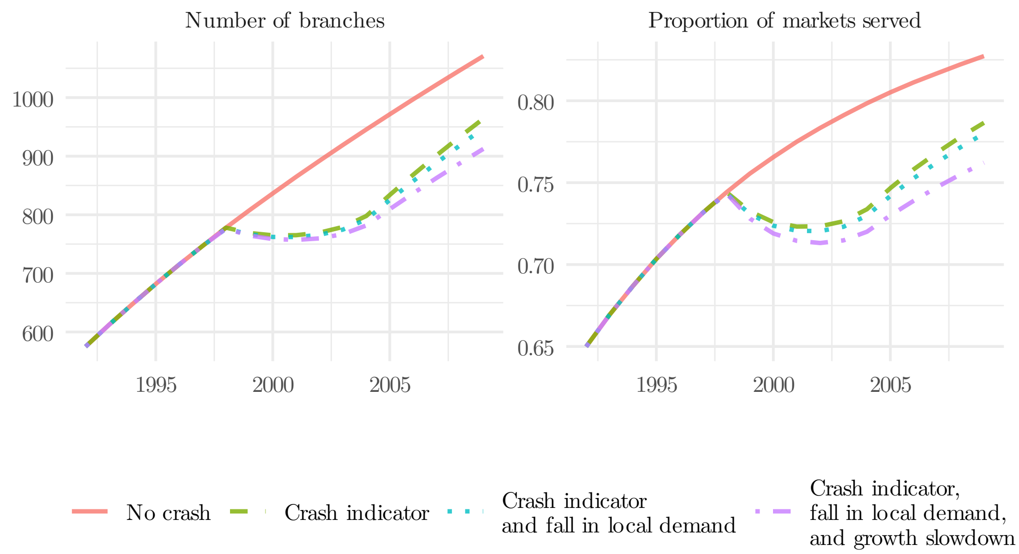


FIGURE A.16: Decomposition of the Crisis

indicator can explain 75.7% of this drop. When local demand also falls in 1997-1998, the fall in the number of branches is 13.1%. When we also add the slowdown in the growth rate of local demand, we obtain the total fall of 15.6%. Therefore the slowdown in the growth rate of local demand after the crisis explains relatively more of the drop than the fall in local demand during 1997-1998. The decomposition for the proportion of served markets shows a similar pattern, with the crisis indicator explaining 69.7% of the drop.