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

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**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 7.2% more branches and 4.8% more markets with at least one branch after ten years in the absence of the crisis. Furthermore, access to loans would have increased by 7.4 percentage points.

*Key words*: Banking, Dynamic Oligopoly, Financial Access

*JEL Codes*: D43, G21, L13, L80

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# 1 Introduction

National financial crises often lead to restricted access to credit for households and firms, which impacts the real economy. Since Bernanke (1983), economists have recognized the increased cost of financial intermediation through the disruption of the banking sector as a major factor in the impact of a crisis. But economists have measured this effect with aggregate measures of economic activity, such as GDP, GDP growth, and interest rates, which typically indicate the effects of the crisis ending within a few years. We identify a new channel by which financial crises impact access to credit that can be much longer-lived: 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, including in present-day developed countries,[1] and access to banking services has also been shown to reduce poverty (Burgess and Pande, 2005; Bruhn and Love, 2014). Two reasons for bank proximity to matter 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 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 led banks to face budgetary con-

[1] See, for example, Herpfer et al. (2023); Nguyen (2019); Agarwal and Hauswald (2010); Ergungor (2010); Assuncao et al. (2024); Alem and Townsend (2014); Ho and Ishii (2011); Petersen and Rajan (2002); Degryse and Ongena (2005); Crawford et al. (2018).

straints. Because branches are typically not direct revenue centers, short-term budgetary constraints 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. As we document, even when entry rates recovered, entry was not always in the places that saw exit. At that point, growth rates were lower and the sunk cost of setting up a new branch may not be warranted. Several communities that experienced exit still have not seen new entry ten years after the crisis. Thus, closures cause long-term impacts in these geographic areas. Because these areas are typically rural or less developed, 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.[2] 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 variation in nighttime light such that our measure of local demand matches changes in real GDP at the provincial level. 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

[2] In this sense, we follow the approach of Sanches et al. (2018), who estimate a dynamic branching model for isolated markets in Brazil. This is in contrast to Kuehn (2018), who allows for cross-market spillovers in branching. As we document below, we find no evidence for cross-market spillovers in branching behavior and opt for this approach to reduce the computational burden in estimation.

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 using a group fixed effects approach. We follow an approach similar to Collard-Wexler (2013) and Lin (2015) to partition markets into ten groups. In our framework, the equilibrium choice probabilities are allowed to differ across market groups 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 term for the crisis in the banks' profit functions. This 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.

Our model provides an explanation for why closed branches were not rebuilt after the crisis. We estimate 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 the branches in many of those locations after the economy recovered.

Our structural model is able to match the 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 quantify the impact of the crisis on branching strategies. We do this by removing the volatility in local demand growth, similar to Collard-Wexler (2013). We set a constant growth rate of local demand for each market such that it matches the overall growth rate during our sample period (1992-2009). We also remove the crisis terms in the banks' profit functions. We then solve for the equilibrium strategies of the banks. Because in this scenario the average growth rate is lower during 1992-1997, fewer branches enter in this time period. However, because there is no volatility, the market does not experience a contraction after 1997. Ten years after the crisis, there would have been 7.2% more branches had there been no volatility in local demand growth. This is significant, as the number of bank branches and bank competition has been linked to improved financial access.[3] We also find that there would have been 4.8% more markets served by at least one branch, and the average distance to the nearest branch would have fallen by 29.1% 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. (2023) to evaluate the effect of demand volatility on financial access in our setting. Using their estimate with our change in distance, access to loans would have increased by 7.4 percentage points. 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.[4] Because these markets are typically less developed, this means our results are particularly pronounced for low-income households.

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 that are at the brink of being unbanked. We define these as markets in the lowest quintile of local demand or market group that have only one branch remaining. 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 1.8% relative to the baseline, but increases the percentage of served markets by 3.3% and financial access by

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

[4] Ji et al. (2023) study Thai branch expansion in the pre-crisis period (1986-1996) and its role in affecting growth and inequality. Another related paper is Assuncao et al. (2024) who study the location strategies of the public-sector Bank for Agriculture and Agricultural Cooperatives during the pre-crisis period (1986-1996). In contrast to these, we study how the 1997 crisis affected the branching strategies of commercial banks and quantify the effect of the crisis on financial access through the branching channel.

5.0 percentage points. In our paper we do not attempt to determine the socially optimal subsidy or the efficient number of branches. This would require detailed knowledge of all the social benefits of branches and their costs. Instead, we aim to quantify the impact of the crisis on financial access through the branching channel, without taking a stance on what allocation of branches is welfare optimal.

**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 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 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; Kuehn, 2018; Sanches et al., 2018; 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, 2023), the Columbian internet market (Hidalgo and Sovinsky, 2025) 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

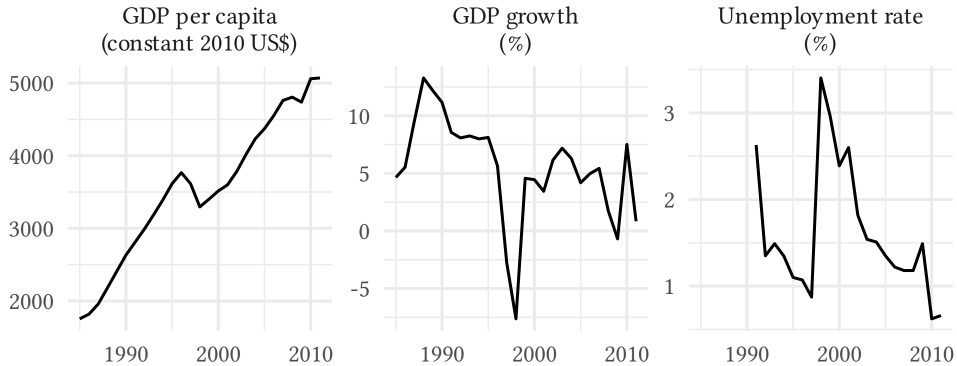
## 2.1 The 1997 Financial Crisis

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 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 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




Data source: World Bank.

FIGURE 1: Thai macroeconomic indicators.

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. There are four large 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 have 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. None are particularly dominant in any specific region.[5] In our modeling, we treat the four largest banks as separate players in our model, but group the remaining 14 smaller banks into a combined fifth fringe player.

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., 2024). The GSB, on the other hand, does locate its branches in more urban areas, with the primary aim of mobilizing savings.[6] There is very little presence of foreign banks outside of the Greater Bangkok Area.

[5]We show a map of all locations held by each bank in Figure A.1 in the Online Appendix.

[6]In Figure A.2 in the Online Appendix we show the number of BAAC and GSB branches over time as well as their locations. No government branches closed during the crisis, but the expansion of their network stagnated until 2005.

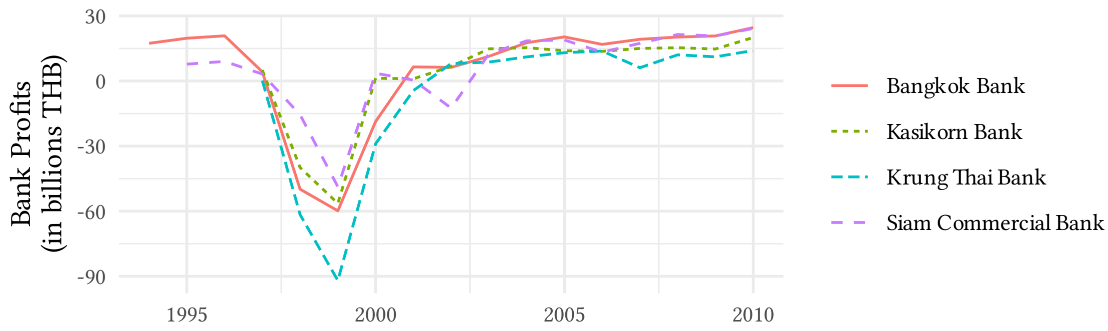



FIGURE 2: Net profit per bank from the banks' annual reports (in billions of Thai Baht).

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.[7] 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.[8]

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 1992 to 2009 in our estimation sample (which we describe in Section 2.3). The crisis had an immediate and dramatic effect on the opening of new branches and the slowdown in openings persisted until at least 2004. 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 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." Because banks were losing profits on aggregate and faced liquidity issues, they were also unable to cross-subsidize loss-making branches with profitable ones.[9]

Although branch openings began to exceed closings by 2004 on aggregate, there were

[7]During this time period, US$1 was on average 36.5 Thai Baht.

[8]In Figure A.3 in the Online Appendix we show the total loans and deposits for the four largest banks. Total loans took until at least 2004 to recover to pre-crisis levels.

[9]In Figure A.4 in the Online Appendix, we show the total number of branches by bank for the sample we use in estimation.

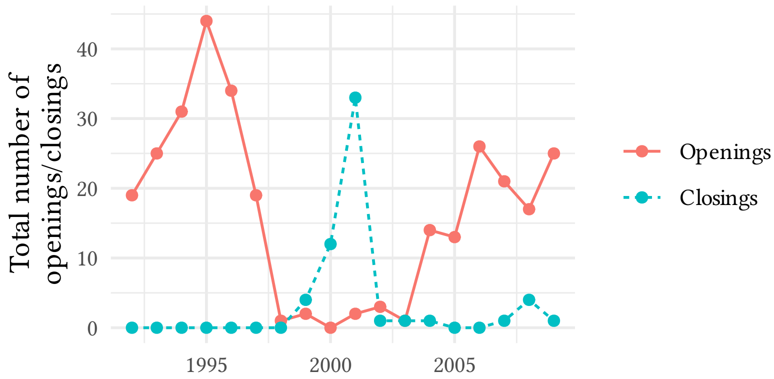



FIGURE 3: Number of openings and closings by year.

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. In our data, a bank re-opened a branch in the same local area where it closed one only 3.8% of the time. 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. 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, the financial crisis can have long-lasting impacts on the development of these locations through the bank branch channel.

We further argue that the closures and slowdown in openings were not due to the industry moving towards digital banking. According to World Bank Data, less than 2% of individuals in Thailand were using the internet during the crisis period. During the early 2000s where we see the largest slowdown in openings and most of the branch closures, internet usage remained below 10%.[10] Rural areas, which are the main focus of our

[10]Source: https://data.worldbank.org/indicator/IT.NET.USER.ZS?&locations=TH.

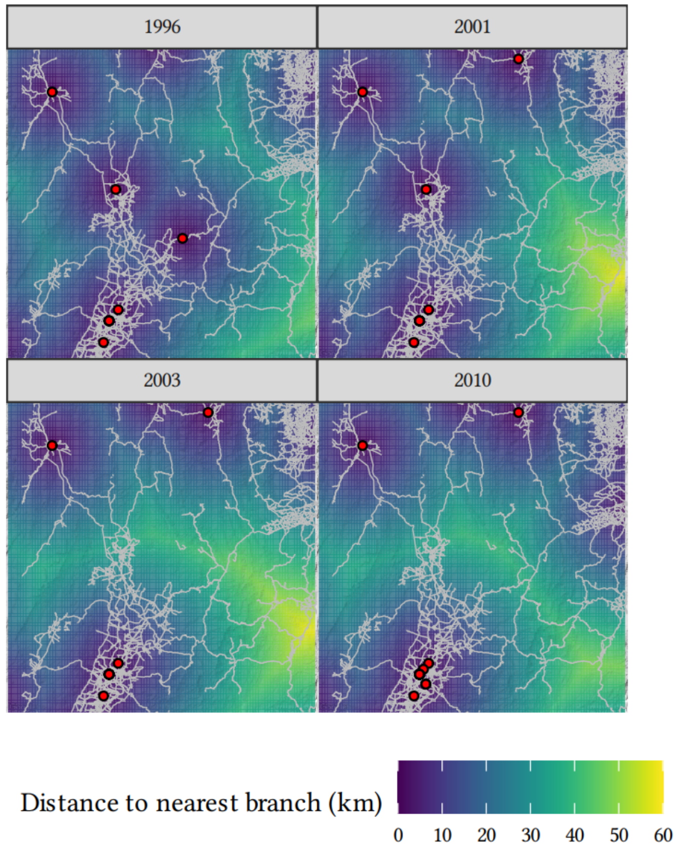



Figure 4: Distance to nearest commercial branch in the Phrae changwat following the financial crisis, 1996, 2001, 2003 and 2010.

analysis, had even lower internet usage.

Finally, we argue that the slowdown in openings and closures beginning in 1999 were not due to other reasons, such as political instability. Our data on bank branches go back until 1927, and only after the 1997 crisis do we observe the first branch exits. In the 70 years until the first exit Thailand went through a large number of unstable periods, including various elections, wars, coups and counter-coups, and a communist insurgency. Therefore we find it unlikely that the large number of closures during 2001-2002 were due to any instability following the 2001 general election. Furthermore, we read the annual reports of the largest four banks for all years we had available and all cite the financial crisis and its aftermath (liquidity issues, non-performing loans, etc.) as the main driver for the banks' financial problems and slowdown in the expansion of their branch network. Some reports refer to reductions in profits arising from global slumps in economic growth negatively affecting Thai firms' exports. However, we account for this in our modeling to the extent that these reductions in exports are captured by local GDP.

## 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 are little demand spillovers between markets. Doing so is more straightforward in rural Thailand than in a developed country because banks are more disperse. However, 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 construct markets, 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*. A branch location can contain multiple branches: the 4,128 commercial branches are in 1,340 branch locations. We define a market as a group of branch locations where every location within the market is within 10km driving distance of at least one other branch location in the same market. We compute the shortest driving distance between branch locations using spatial road network data from OpenStreetMap and the Dijkstra shortest path algorithm. If a single branch location is more than 10km from every other branch location in the country, then that location is in a market by itself. If two branch locations are within 10km of each other but neither of the two are within 10km of any other location in the country, those two locations form a single market. If three branch locations were in a straight line, each 9km from each other, then all three would form a single market, even though the two branches on either end are 18km away from each other.

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

Figure 5 shows an example of our clustering approach in the south of Thailand. The road network data we use are shown by the thin gray lines. Points within the same dia-

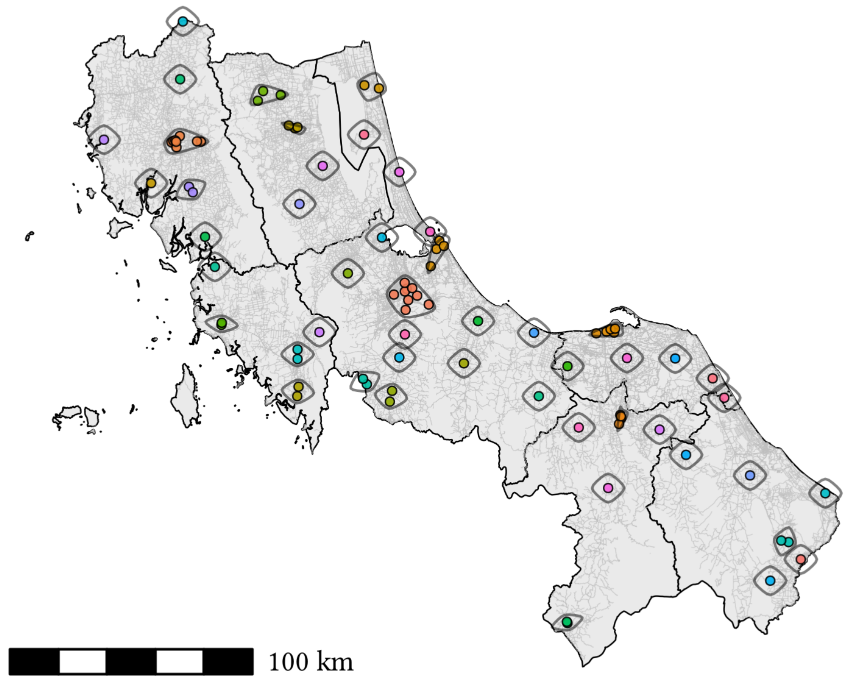



FIGURE 5: Example of clustering locations into markets in Southern Thailand.

mond 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, this approach generates 589 markets.[11] To ease the computational burden in estimation, we assume in our model that a bank in a market can open or close at most one branch per year and can have at most two branches at any given time. We therefore omit 111 markets where one of the four largest banks or fringe bank had more than two branches at any point in time and six additional markets where one of the banks opened more than one branch in a single year. We estimate our model with the remaining 469 markets.

The locations of all the markets we use in estimation are shown in Figure 6. The average aerial distance to the nearest other market is 20.9km. We show histograms of the number of active branches and the number active banks in Figure A.5 in the Online Appendix. The average number of branches in the market-years we use in estimation is

[11]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.

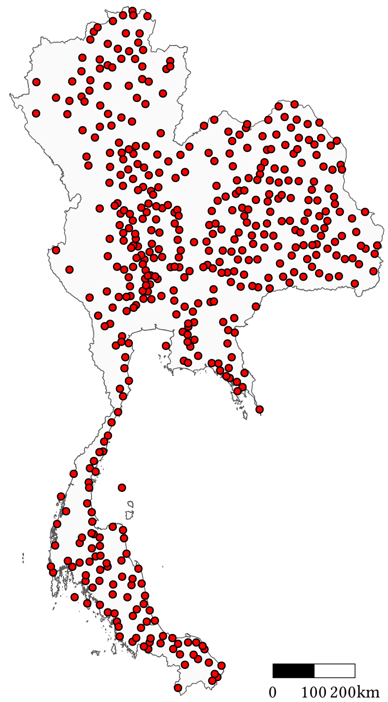



FIGURE 6: Centroid of market locations used in estimation.

1.46, with 69.4% of market-years having at most one branch. Only 7.6% of market-years have four or more branches. Because of this, the vast majority of markets we use in estimation can be described as rural.

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 and obtain almost identical results. These are discussed further in Section 7.

## 2.4 Measuring Local Demand

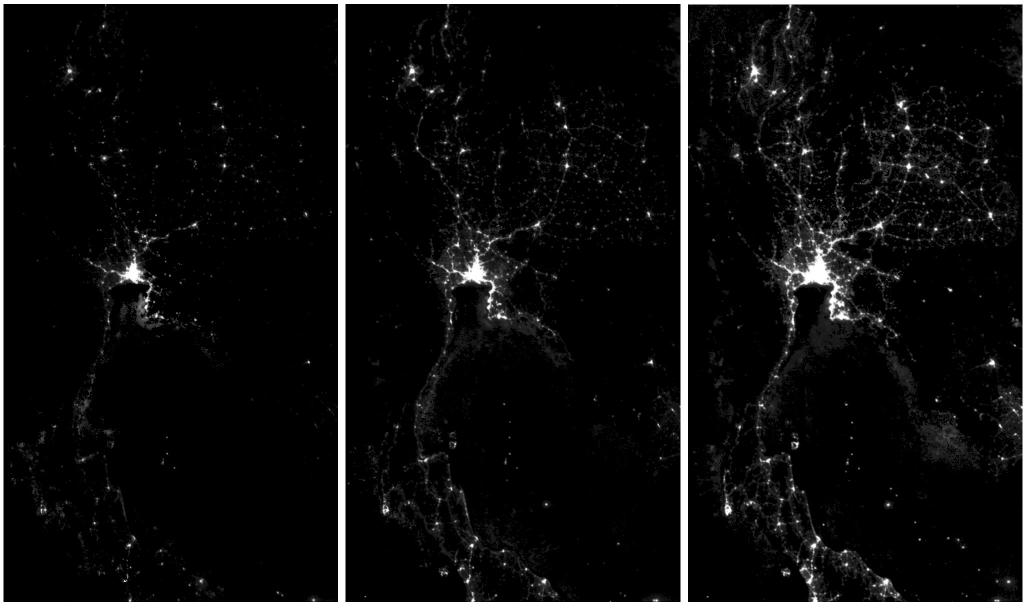
In our model, branch profits in a market depend on the level of local demand in the market. However, standard proxies for local demand such as population or local GDP are not readily available at a fine geographic level for Thailand. We instead use nighttime luminosity data from the National Oceanic and Atmosphere Administration to proxy market attractiveness. These data have been used as proxies for population and income in a large number of applications (e.g. Henderson et al., 2012; Michalopoulos and Papaioannou, 2013).

Hu and Yao (2022) also find that nighttime lights can even be more precise than administrative data in low and middle income countries. 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 represented on a grid with a 30 arc-second resolution. A 30 arc-second resolution in Thailand implies that each data point measures nightime light in an area of approximately 900m×900m. Because our branching dataset ends in 2010, we constrain our sample period in estimation to 1992-2010, the overlap of the branching data and nighttime light data.

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.[12]

Because our structural model uses both temporal variation in nighttime luminosity within markets, as well as cross-sectional variation across markets, it is necessary to first intercalibrate the digital number values (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. Furthermore, different industries across regions may emit more or less nighttime light, yet not reflect differences in local GDP. We intercalibrate the nighttime luminosity values using provincial GDP data. Let $Y_{pt}$ be Thailand's provincial real GDP in province $p$ in year $t$ and let $NL_{pt}$ be the total sum of nighttime luminosity values within province $p$'s borders in year $t$. When two satellite readings covering the same year are available, $NL_{pt}$ is the average

[12]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.



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

FIGURE 7: Raw nighttime luminosity data over time.

of the two satellites. We calculate a multiplier for each province-year according to:

$$\kappa_{pt} = \frac{Y_{pt}}{NL_{pt}} \tag{1}$$

We then multiply all the nighttime luminosity values in the raw cell-year nighttime luminosity data with the corresponding multiplier. The multiplier ensures that provincial nighttime luminosity follows the same trend as provincial GDP.

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 intercalibrated nighttime luminosity digital numbers within that circle.[13] 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 $(x_m, y_m)$. Furthermore, let the function $\widetilde{p}\,(x, y)$ return the province $p$ in which coordinate pair $(x, y)$ is located. Local

[13] 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.

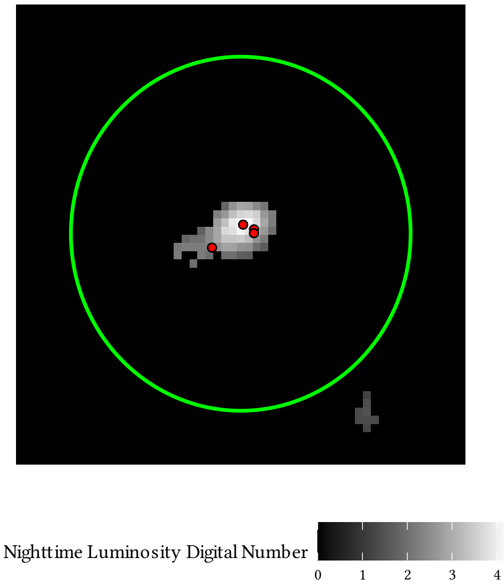



Figure 8: Night lights within a 20km radius of market centroid.

demand for market $m$ at time $t$ is then:

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

where $nl_t(x, y)$ is the nighttime luminosity digital number at point $(x, y)$ at time $t$.[14]

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 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 intercalibrated nighttime luminosity digital numbers in the entire circle. For the markets we use in estimation, each branch location is at most 6.2km from the market centroid, and therefore this 20km radius always includes all branch locations within the market.

To evaluate how well province-intercalibrated nighttime luminosity captures local demand at a more granular level, we compare the sum of the luminosity values in a dis-

[14] 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.

trict to the district population from the 2000 and 2010 censuses. Excluding the Bangkok Metropolitan Region, this includes 878 districts. Apart from a small number of districts, the measure performs very well at predicting population levels and has a correlation of 0.63. The measure is less accurate at predicting the small number of very large within-district increases in population, but is still strongly positively correlated in changes. Scatter plots of the two variables in levels and changes are shown in Figure A.6 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 and allowing 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 very 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 size of the state space and as a result 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 depend 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:

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

Each market $m$ belongs to one of $K$ groups, and we use group fixed effects $\theta_{k(m)}$ in the profit function to capture persistent unobserved heterogeneity across market groups, $k = 1, \ldots, K$. The per-branch profit also differs by bank and this is captured by $\theta_f^b$, for $f = 2, \ldots, F$, where we make the normalization $\theta_1^b = 0$ for bank 1. The parameter $\theta^{own}$ 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 $\theta^{comp}$ measures the competitive effect of branches from rival banks in the same market.[15] We allow for the presence of a government bank branch in the market to impact profits using the indicator $g_{mt} \in \{0, 1\}$. The variable $z_{mt}$ is our measure of local demand that affects branch profits. Finally, the variable $\zeta_t \in \{0, 1\}$ is an indicator for the financial crisis and the parameter $\theta^{crisis}$ measures the effect of the financial crisis on profits that is not captured by changes in local demand $z_{mt}$. For instance, during a financial crisis, banks may stop making loans to each other, and thus banks cannot make loans or investments that may be profitable in the long-run, including keeping branches open. This parameter captures the effect of the banks' lower liquidity on their payoffs.[16] The market state, $\boldsymbol{s}_{mt} = \left(\left\{n_{fmt}\right\}_{f=1}^F, g_{mt}, z_{mt}, m, t\right) \in \mathcal{S}$, is the combination of each bank's number of branches, $\left\{n_{fmt}\right\}_{f=1}^F$, government bank presence $g_{mt}$, local demand, $z_{mt}$, and the market and time period.

[15]In principle we could allow for the effect of competition to decay with distance within a market as in Seim (2006). However, this would greatly increase the size of our state space, as we would need to track the number of rival branches at each distance band instead of the overall number. Moreover, because only 10.3% of bank-market-years we use in estimation have more than 2 rivals (and only 4.5% with more than 3), we would unlikely be able to estimate this rate of decay precisely.

[16]In Online Appendix A.6, we show our estimation results and counterfactual experiments from an alternative specification where the effect of the crisis is allowed to change over time within the crisis period. As a further robustness check, we also consider alternative timings of the crisis.

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.[17] 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 $\zeta_t$ 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.[18] 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 $\zeta_t$. 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 $\zeta_t$. 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 $\tau$, $f_t(\tau) = \zeta_\tau$ for $t > 1997$ and $\tau \geq t$. We believe this specification of beliefs is realistic and we have found that this choice produces aggregate branching patterns that best match the patterns in the data. We assume the crisis lasts until 2004 because the observed slowdown in entry lasted this long (see Figure 3). In addition, we also found that this specification produced the best fit with our data.[19]

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 $z_{m\tau+1} \sim h_t(\boldsymbol{s}_{m\tau})$ for $\tau = t, \ldots, T-1$. This specification allows beliefs to change over time in ways that banks do not anticipate. In our implemen-

[17]To test this assumption, we estimate an ordered probit model analagous to our structural model and show that adding the number of own branches, the number of rival branches and government branch presence in a 50km or 100km radius around the market (exluding the market itself) leads to statistically insignificant estimates, and has virtually no effect on the within-market estimates. We show these results in Table A.1 in the Online Appendix. This suggests that banks' entry-exit decisions in a market does not depend on branching in nearby markets.

[18]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.

[19]We also show evidence in Figure A.11 in the Online Appendix that allowing the crisis to last a different number of periods has only small effects on the other parameter estimates.

tation, 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 $h_t(\cdot)$ 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 group $k(m)$, and the number of bank branches in the market. This last dependency allows the presence of banks to affect local demand growth.[20] Finally, recall that banks in all periods $t$ believe that $z_{m\tau+1} = z_{m\tau}$ for all $\tau \geq T$.

Similar to local demand $z_{mt}$, banks at time $t$ believe that government bank presence in period $\tau > t$, $g_{m\tau}$, follows a Markov process $g_{m\tau+1} \sim \widetilde{g}_t(\boldsymbol{s}_{m\tau})$. The probability of a government branch opening depends on local demand and commercial branch presence. Consistent with the data, government branches do not close, so if a government branch is present, banks believe it will remain present forever.

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 $N = 2$ 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 $t$,

[20] Because of this, our model can capture within-market contagion effects from branch closures, as these would lower local demand growth, making further branch closures more likely.

$\mathcal{A}\left(n_{fmt}\right)$, therefore depends on their existing number of branches:

$$\mathcal{A}\left(n_{fmt}\right) = \begin{cases} \{0,1\} & \text{if } n_{fmt} = 0 \\ \{-1,0,1\} & \text{if } n_{fmt} = 1 \\ \{-1,0\} & \text{if } n_{fmt} = 2 \end{cases} \tag{4}$$

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 $\theta^{ec}$. The scrap value from closing a branch is normalized to zero because it would not be separately identified from the entry cost, $\theta^{ec}$, and the group fixed effects, $\theta_{k(m)}$.[21] We recognize that such a normalization is not innocuous for our counterfactual simulations (Aguirregabiria and Suzuki, 2014; Kalouptsidi et al., 2024, 2021). We show that our main results are robust to this normalization in Section 7. Banks also receive action-specific private information shocks $\boldsymbol{\varepsilon}_{fmt} = \left(\varepsilon_{fmt}^{-1}, \varepsilon_{fmt}^{0}, \varepsilon_{fmt}^{1}\right)$ 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:

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

[21] We do not allow the cost of entry to change during the crisis, as this would be difficult to identify separately from the $\theta^{crisis}$ parameter. If entry costs increased during the crisis, this would be captured by $\theta^{crisis}$. Similarly, if entry costs vary by market group, this would be captured by the $\theta_{k(m)}$ terms.

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 $\zeta_t$ (governed by $f_t(\cdot)$), beliefs about the transitions of government banks (governed by $\widetilde{g}_t(\cdot)$), and the beliefs about local demand (governed by $h_t(\cdot)$). The future transition probabilities of $g_{mt}$ and $z_{mt}$ also depend on the banks' strategies, as the number of branches can impact government branch entry and 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, $V_f(\boldsymbol{s}_{mt}, \boldsymbol{\theta}) = \int_{\boldsymbol{\varepsilon}} \widetilde{V}_f(\boldsymbol{s}_{mt}, \boldsymbol{\varepsilon}_{fmt}, \boldsymbol{\theta}) f_\varepsilon(\boldsymbol{\varepsilon})\, d\boldsymbol{\varepsilon}$, where $f_\varepsilon$ is the joint density of the shocks. Because $\varepsilon^a_{fmt}$ is distributed Type I extreme value, the expected value function before the realization of the private information shock is given by:

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

where $\gamma \approx 0.577$ is the Euler-Mascheroni constant. Similarly, before the realization of the private information shock, the probability that bank $f$ chooses action $a \in \mathcal{A}(n_{fmt})$ in market $m$ at time $t$ is given by:

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

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

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

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 group fixed effects, and banks' differing histories in entry.[22]

# 4 Estimation

## 4.1 Market Group Fixed Effects

Controlling for persistent unobserved market heterogeneity is important for obtaining useful estimates from an entry model. In addition to controlling for local demand, we allow markets to have heterogeneous market groups that make them more or less attractive for opening bank branches. Some researchers perform the classification of markets into groups and structural estimation in seperate steps (e.g. Collard-Wexler, 2013; Lin, 2015), whereas others do this jointly (e.g. Igami and Yang, 2016). We choose to do this separately to ease computation. We classify each market into one of ten groups. The reason we use ten groups is because when we estimate our structural parameters, we need to solve the dynamic game separately for each market group for every trial value of the parameter vector. Additional groups increase both the number of parameters we need to search over and the number of times we need to solve the model for each trial value. We choose to use ten groups to balance the computational burden and being able to flexibly control for persistent unobserved market heterogeneity.[23] We obtain these groups by using the es-

[22]We also checked if the resulting value functions at the estimated parameters were decreasing in the number of rival branches. We plot this in Figure A.7 in the Online Appendix.

[23]In Figure A.8 in the Online Appendix we explore how the number of market groups affects the parameter estimates in an analgous reduced-form version of our structural model. We find that using ten groups

| *Dependent variable:* | Enter (1)<br>Nothing (0)<br>Exit (−1) |
|---|---|
| Own branches | −1.439 |
| | (0.076) |
| Rival branches | −0.559 |
| | (0.039) |
| Government Bank Presence | −0.182 |
| | (0.310) |
| Local demand | 0.971 |
| | (0.162) |
| Observations | 42210 |
| Market fixed effects | Yes |

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

TABLE 1: Ordered Probit results.

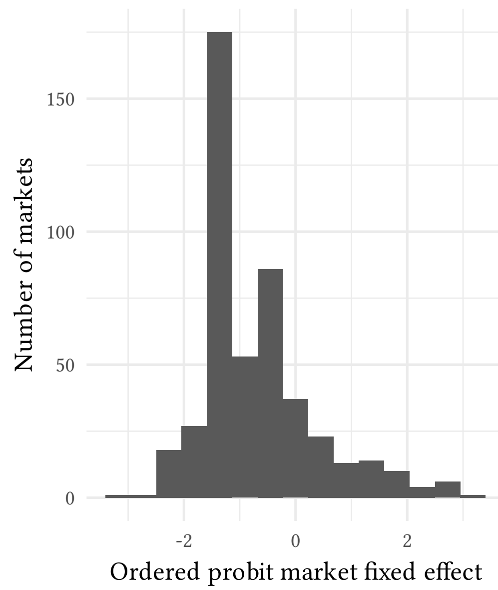



FIGURE 9: Market fixed effects.

timated market fixed effects from an ordered probit regression at the bank-market-year level using our entire sample period. 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, government bank presence, 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. Government branch presence has a negative effect but is not statistically significant. Figure 9 shows a histogram of the estimated market fixed effects from this regression. These market fixed effects capture the time-invariant unobserved factors that make certain markets, conditional on local demand and the existing number of own and rival branches, experience more entry (and less exit) than others. We divide markets into ten equally-sized categories based on the value of the estimated market fixed effects, with market group 1

brings the parameter estimates very close to using many more groups (such as 50) while retaining computational tractability. This is evidence that using 10 groups purges much of the unobserved heterogeneity across markets.

having the smallest values. Each market fixed effect is estimated with 90 observations (5 banks and 18 time periods). Therefore we argue that these effects are estimated precisely enough to be able to classify markets into 10 groups. We use the market groups in our structural model to capture persistent unobserved heterogeneity between markets that is not captured by our measure of local demand.

In Figure A.9 in the Online Appendix, we show that our results are unlikely to be driven by bank behavior in one particular year. We estimate a reduced-form analagous version of our structural model each time omitting one year of data. Although there are small differences, none are statistically different. In Figure A.10 in the Online Appendix, we show a map of the market groups. The map shows that all market groups can be found all over the country and not clustered in certain areas.

## 4.2 State Transition Processes and Beliefs

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

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

where $\nu_{mt+1} \sim \mathcal{N}\left(0, \sigma_\nu^2\right)$. Local demand changes are allowed to vary by market group, $k$, the number of active bank branches $\sum_{f=1}^{F} n_{fmt}$, and government branch presence $g_{mt}$. Under this specification, newly entering branches do not affect local demand immediately, but only with a one-year lag. We observe a downward shift in local demand in all markets during 1997 and 1998 which we capture with the $\delta_{96}$ and $\delta_{97}$ terms. We also allow the market group 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. Rural-to-urban migration is reflected in $z_{mt}$ and so $\eta_{k(m)}$ can capture any differential patterns in rural-to-urban migration across market groups, and the $\eta_{k(m)}^{post}$ terms can capture how these change differentially after the crisis.[24]

[24] Allowing the market group fixed effects in the local demand transition equation to change after the crisis adds flexibility to our structural model without increasing the computational burden. The reason we do not additionally allow the market group fixed effects in our structural model to also change is because this would greatly increase the number of parameters we need to estimate, and hence increase the computational

The regression estimates of this equation are shown in Table A.2 in the Online Appendix. The regression shows that the $\eta_{k(m)}$ terms for all market groups fell after the crisis. We also estimate negative coefficients on the crash years, which capture the level drop in GDP that we observe in Figure 1. The total number of active branches and government branch presence in a market also have positive and significant effects on the level of local demand in the following period.[25] 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, $h_t(\boldsymbol{s}_{m\tau})$, 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 $t \leq 1997$, $h_t(\boldsymbol{s}_{m\tau})$ is given by:

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

for all $\tau$, 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, $h_t(\boldsymbol{s}_{m\tau})$ is given by our estimates of equation (10) for all $t > 1997$.[26]

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-group effects are meant to address this but we take up this issue further in our robustness discussion in Section 7.

Finally, for how commercial banks form beliefs over the future presence of government branches, we estimate a logit model predicting the entry of a government branch in a market using local demand and the number of commercial branches. We do not solve

burden substantially.

[25] Although market groups 1-2 have fewer branches compared to others, the estimated $\eta_k$ terms are largest for these. Higher market groups on average have more branches, but do not necessarily have larger local demand. This is because the market groups capture unobserved factors driving entry conditional on local demand. Furthermore, these results also do not mean that markets in groups 1-2 on average grow faster – they only grow faster conditional on the number of branches, which is on average smaller for these groups.

[26] Although we assume that the crisis indicator $\zeta_t$ 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.

for a model of government optimization. This way, we are agnostic about whether government banks are profit maximizing or have another objective function. Because we do not observe any exit of government branches, we assume entry is an absorbing state for government branches. Table A.3 in the Online Appendix shows the regression estimates. Government branches are more likely to enter in markets with greater local demand, and less likely (although not statistically significant) to enter in markets with more commercial branches. In our counterfactual simulations, we assume government banks continue to transition according to this process.[27]

## 4.3 Structural Parameter Estimation

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

$$\boldsymbol{\theta} = \left( \{\theta_k\}_{k=1}^{k=10}, \left\{\theta_f^b\right\}_{f=2}^{f=5}, \theta^{own}, \theta^{comp}, \theta^{gov}, \theta^{z}, \theta^{crisis}, \theta^{ec} \right) \tag{12}$$

We do not estimate the annual discount factor but rather 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; 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 20 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 group. 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. To obtain the equilibrium choice probabilities at the actual levels of local demand, we use linear interpolation. We provide further details on this procedure in Online Appendix A.2.

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 group $k$ at time $t$ in the data, where the

[27] We are aware that under a counterfactual policy, government banks may change their branching patterns with respect to these state variables. However, because the government banks did not close any branches during the crisis, we find it reasonable to assume their strategies with respect to the state variables would be similar in the absence of the crisis.

sample period is 1992 to 2009. The maximum likelihood estimator of $\boldsymbol{\theta}$ is then:

$$\widehat{\boldsymbol{\theta}} = \arg\max_{\boldsymbol{\theta}} \sum_{t=1992}^{2009} \sum_{m=1}^{M} \sum_{f=1}^{F} \log \left( p_f \left( a_{fmt} \,|\mathbf{s}_{mt}, \boldsymbol{\theta} \right) \right) \tag{13}$$

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

# 5 Model Estimates

Table 2 shows the structural parameter estimates. As in Table 1, branch profits are increasing in local demand and are decreasing in the presence of own and rival branches. Like Igami and Yang (2016), we also find that the cannibalization effect is stronger than competition from rival branches ($\widehat{\theta}^{own} < \widehat{\theta}^{rival}$). The value of $\widehat{\theta}^{rival}$ is 22.7% of the average model profit for a branch in 2005. One reason for this lower diversion rate could be high borrower switching costs due to relationship lending. Kim et al. (2003), for example, estimate that switching banks on average costs about one-third of the market average interest rate on loans. The estimated effect of the crisis shows a large decrease in profits, much greater than the presence of rival branches. The estimated group fixed effects are monotonically increasing in the group index, in line with the values from the ordered probit market fixed effects. The impact of government branch presence is very close to zero, and not statistically significant. The estimates of the bank-specific profit shifters $\theta_f^b$ are close to zero (relative to the Krung Thai Bank) for two of the larger banks and negative for the smaller Siam Commercial Bank (bank 4) and the fringe bank (bank 5).

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.12 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. Figure A.13 in the Online Appendix shows the same but split by market group. The model matches the total number of branches by market group well for most groups. In Figure A.14 in the Online Appendix, we also show how the total number of branch openings and closings per year predicted by the model compare with the data. In general,

| | Estimate | Standard Error |
|---|---|---|
| Entry cost | 11.749 | (0.314) |
| Market group 1 | 0.156 | (0.089) |
| Market group 2 | 0.253 | (0.089) |
| Market group 3 | 0.289 | (0.097) |
| Market group 4 | 0.326 | (0.107) |
| Market group 5 | 0.341 | (0.091) |
| Market group 6 | 0.387 | (0.090) |
| Market group 7 | 0.440 | (0.087) |
| Market group 8 | 0.502 | (0.088) |
| Market group 9 | 0.614 | (0.093) |
| Market group 10 | 0.878 | (0.101) |
| Bank 2 | −0.001 | (0.011) |
| Bank 3 | 0.000 | (0.011) |
| Bank 4 | −0.065 | (0.012) |
| Bank 5 | −0.053 | (0.011) |
| Local demand | 0.475 | (0.054) |
| Own branches | −0.126 | (0.009) |
| Rival branches | −0.104 | (0.009) |
| Government branches | 0.000 | (0.087) |
| Crisis | −0.549 | (0.080) |

Table 2: Structural parameter estimates.

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.[28]

# 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. We then simulate the effect of bank branch supports during the crisis on improving financial access both during and after the crisis.

[28] In Figure A.15 in the Online Appendix we also compare the transition matrices predicted by our model to the data for the total number of branches in a market for different years, for both above- and below-median income markets. The model is able to reproduce the general patterns in the data well. Additionally, we show the total annual bank profits predicted by the model in Figure A.16.

## 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.

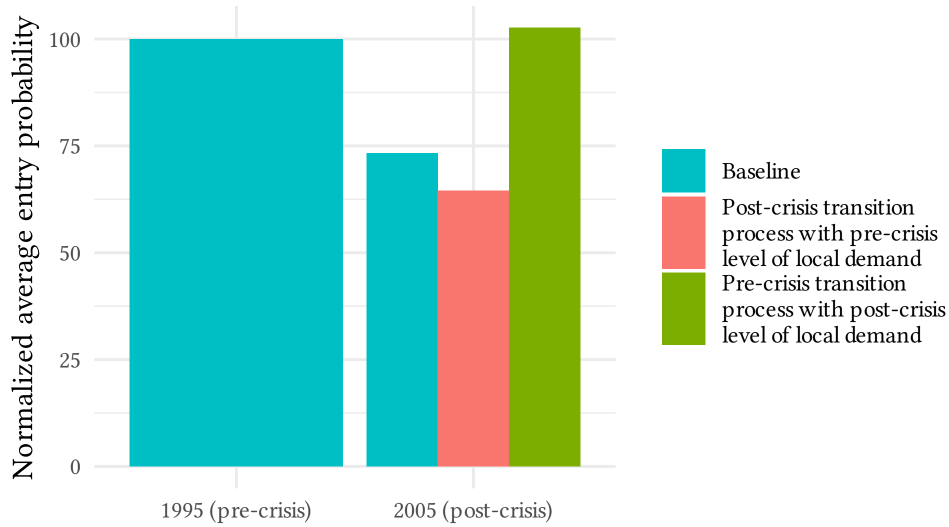
Part of this slow recovery is the large cost of opening a branch relative to the per-period profits of a branch. According to the estimated model in 2005, the average branch earned profits of 0.461. Thus the estimated entry cost is 25.46 times this.[29] Even though a rural branch that closed during the 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 38.5% 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 attractive for banks to open branches in these locations in the future.[30]

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 mar-

[29] In Online Appendix A.3 we provide a discussion on why we do not view this number as unrealistically large.

[30] To provide evidence for this contagion effect, in Table A.4 in the Online Appendix, we regress the entry probability according to our model on whether a market has fewer than its previous peak number of branches, controlling for local demand, the number of own and rival branches, government branch presence, the crisis indicator, bank fixed effects and market group fixed effects. We find that having lost branches lowers the entry probability by about one half. The results also hold if we instead control for year fixed effects instead of the crisis indicator.




The blue bars show the normalized average entry probabilities in 1995 and 2005 in markets groups 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.

kets more vulnerable to becoming unbanked and focus on market groups 1-3.[31] In Figure 10 we show the average entry probabilities from our model 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 26.7% between 2005 and 1995 in these markets, despite the fact that local demand in 2005 was on average 25.4% higher. This is shown by the blue bars in Figure 10. If local demand was at its 1995 level in 2005, the average entry probability would have been 35.47% 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 2.6% larger in 2005 compared to 1995. This is shown by the green bar in Figure 10. This increase

[31]The results that follow also hold when we look at other groupings of market groups, such as 1-2, 1-4, or all ten market groups.

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.[32]

### 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. One approach to do this would be to set the crisis indicator $\zeta_t$ equal to zero and use the pre-crisis process of local demand for all time periods, and then solve for the equilibrium strategies of the banks. Under this approach, the crash does not occur and firms do not place a positive probability of it occurring in the future. However, arguably the high growth rates before the crisis were unsustainable and it is unreasonable to assume these could be maintained over a long-term horizon. Therefore in this counterfactual, we consider the impact of a less volatile growth path on branching strategies. We consider the impact of a stable growth rate throughout the entire sample period that results in the same aggregate level of GDP in 2009 as in our baseline case but without a crisis. We then estimate the impact of such a policy on branching strategies.[33]

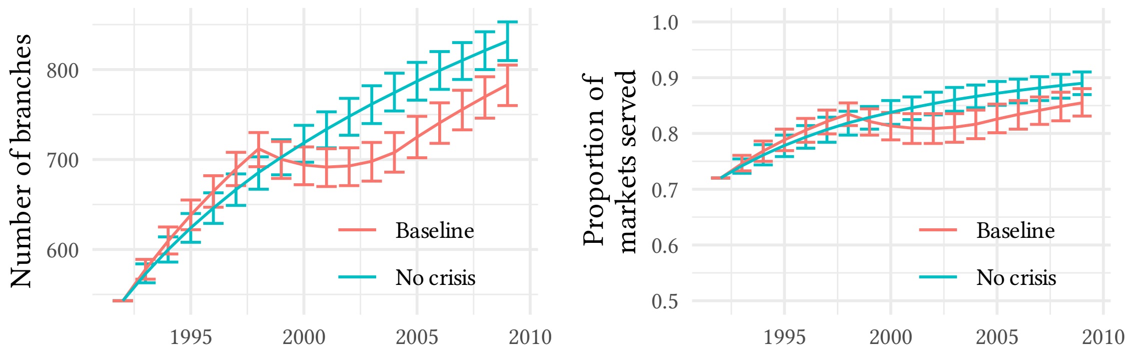
We implement this counterfactual as follows. We use the following local demand transition function for the entire sample period:

$$z_{mt+1} - z_{mt} = \eta^{\star}_{k(m)} + \alpha^B \sum_{f=1}^{F} n_{fmt} + \alpha^G g_{mt} + \nu_{mt+1} \tag{14}$$

where we solve for the $\eta^{\star}_{k(m)}$ for each market group, $k$, that produces an average market-group-level local demand in 2009 across simulations that matches the baseline case. We use the bisection method to solve for each of the $\eta^{\star}_{k(m)}$. Because the transitions of local demand depend on the banks' branching strategies, we also solve for the equilibrium

[32]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, which should have increased entry. Therefore we do not believe these requirements caused the entry patterns to change.

[33]In Online Appendix A.4 we present results from a counterfactual experiment where the crash does not occur and growth continues according to its pre-crisis trend.




(A) Number of active branches.

(B) Proportion of served markets.

FIGURE 11: No crash scenario versus baseline scenario.

strategies for each trial value of $\eta^\star_{k(m)}$. The mean $\eta^\star_{k(m)}$ from this procedure is $-0.0048$, which is in between the pre-crisis mean of 0.0020 and the post-crisis mean of $-0.0071$ in the baseline case.

Using the $\eta^\star_{k(m)}$, we solve for the equilibrium branching strategies and simulate entry and exit 1,000 times. Figure 11 shows the results. Figure A.24a 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. Because of the lower growth rate of local demand, fewer stations enter pre-crisis compared to the baseline case and correspondingly fewer markets are served by a bank. However, the trend of entry continues throughout the entire sample period instead of falling during the crisis period. By 2007, ten years after the crisis, there are 7.2% more branches. In Figure A.17 in the Online Appendix, we show the average number of entries and exits by year from our simulations. From this we can see that the slowdown in openings is the main cause of the reduction in number of branches from the crisis, but the closures caused by the crisis also contributed significantly to this.

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 A.24b, 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

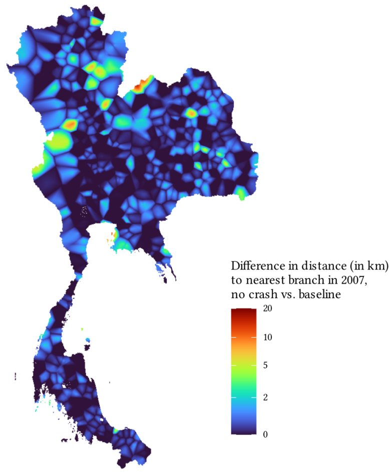



FIGURE 12: Effect of the crisis on distance to the nearest branch.

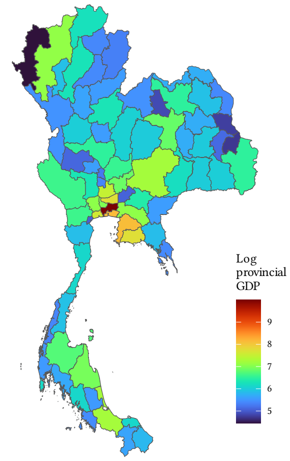



FIGURE 13: Provincial GDP in 1996 (for comparison).

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 4.8% more markets served by 2007 compared to the baseline scenario.

Markets that 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. Although we exclude a subset of markets in estimation, we use the full set of 589 markets to perform this calculation. Figure 12 shows the change in distance to the nearest branch on average from our simulations, with Figure 13 showing the provincial GDP in 1996 next to it for comparison purposes. Many locations saw an increase in distance with some locations seeing an increase of up to 20km.

Ji et al. (2023) estimate a regression model using Thai data explaining the access to loans by the distance to the nearest branch. Using their estimated effect with our predicted change in distance of 29.1%, village access to commercial loans would have been 7.4 percentage points higher in the absence of the crisis, over a baseline percentage with access of 43.6% in 1996.[34] In Figure A.18 in the Online Appendix, we show the effect of the crisis split by income quartiles. Each quartile is affected similarly in terms of the number of branches, but lower-income quartiles are more affected in terms of the proportion of markets served by a branch. This shows that the crisis increased access inequality across

[34] Access to commercial loans in Ji et al. (2023) is a dummy variable which equals one if the village head stated that households in the village had obtained loans from a commercial bank.

regions. We also decompose the effects of the crisis indicator and the change in the local demand transitions in Online Appendix A.5.

## 6.3 Targeted Branch Supports

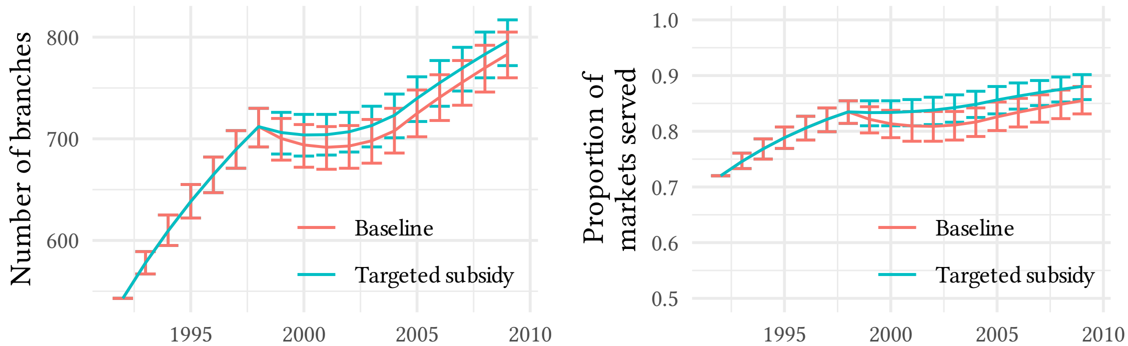
We now consider the effect of bank branch supports on maintaining the branch network during the crisis. During the crisis, banks faced liquidity issues and closed branches in many locations. After the crisis was over, banks often never reopened the closed branches, even though those branches may have had positive profits after the crisis was over. This is because of the large entry cost of opening a branch, and because 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 and being in either lowest quintile of local demand or market group (i.e. market groups 1-2). For branches in these markets, we consider a subsidy equal to $-\theta^{crisis}$ for the years where the crisis indicator, $\zeta_t$, equals one.[35] Although this subsidy does not compensate branches entirely for the decrease in local demand and subsequent slowdown in growth, it compensates banks for a considerable portion of the losses.[36] 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.

The results are shown in Figure 14, presented in the same format as Figure 11 for ease of comparison. Figure 14a shows that although the total number of branches did not continue according to its pre-crash trend, the total size of the branch network only experienced a brief small contraction following the crisis. Ten years following the crisis, the total number of branches is approximately 1.8% higher compared to the baseline scenario. Similarly, Figure 14b shows that the subsidy prevented the proportion of served markets

[35] Because only the last remaining branch in a market receives the subsidy, this subsidy can create a war of attrition between the remaining branches in a market.

[36] This is based on our decomposition of crisis effects shown in Online Appendix A.5.




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

FIGURE 14: Branch network expansion under bank branch support subsidy versus baseline.

from decreasing. By 2007, the proportion of served markets was 3.3% higher compared to the baseline.

Based on our simulations, between 94 and 103 branches receive the subsidy each year, where the cost per branch is approximately 18.5% more than the predicted average per-branch profit in 2005 (the first year after the crisis).[37]

# 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.19 in the Online Appendix shows the differences between the clustering approaches for the branch locations in Southern Thailand. We also proportionally adjust the radius that we use to calculate local demand. In Table A.5, we show the structural estimates and effects of the crisis under each approach. Both the structural parameter estimates and estimated effects of the financial crisis are very similar under each radius.

In our baseline model specification, we allow banks to internalize the effect of their

[37] Although this subsidy is quite large, one reason for why more branches do not close in the absence of the subsidy is because banks are forward looking in our model. Many banks choose to suffer some losses throughout the crisis because they will earn positive profits afterwards. Only banks suffering very large losses are pushed over the threshold for closure.

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 and government branch presence as regressors. The structural estimates using this transition process are shown in Table A.6. 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 and obtain very similar effects, which are summarized in Table A.6.

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 group fixed effects ($\theta_{k(m)}$) that we include. We test the sensitivity of our results to possible upward bias in the estimated coefficients on the total number of branches and government bank presence in Table A.2 by setting the coefficients to half their size and reestimating our structural parameters. The results are shown in Table A.7. 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 large banks and fringe bank 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 set of strategies remains the same, but the monopolist bank can have up to 10 branches per market instead of 2. The estimates are shown in Table A.8 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 smaller than in the baseline specification. For the no-crisis counterfactual, 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 (6.89% more versus 7.22% in the baseline specification).

We normalize the scrap value of exiting to zero as it is not separately identified from the cost of entry, $\theta^{ec}$, and the market group effects, $\theta_{k(m)}$. However, researchers have documented that it is possible that the value of the normalization can have an impact on counterfactual simulations (Aguirregabiria and Suzuki, 2014; Kalouptsidi et al., 2024, 2021). Similar to the approach taken by Igami and Yang (2016), we show that our main results are robust to this normalization by simulating branching according to the baseline model and no-crisis counterfactual under alternative scrap value normalizations. We do this for all integer scrap values between 1 and 10. For each scrap value, $\theta^{sv}$, we adjust the entry cost according to $\theta^{ec}+\theta^{sv}$ and the market group effects according to $\theta_{k(m)}+(1-\beta)\,\theta^{sv}$. We use the same $\eta^{\star}_{k(m)}$ as in the baseline specification. We show the results in Figure A.20 in the Online Appendix. The results are very similar under every normalization. In addition to this, we re-estimate all parameters under the assumption $\theta^{sv}=1$, and solve for the $\eta^{\star}_{k(m)}$ under these estimates. The results are shown in Table A.9 in the Online Appendix. Although the structural estimates differ, the estimated impacts of the crisis are very similar to our baseline results.

In our baseline specification, the crisis term $\zeta_t$ equals one in years 1998-2004 and is zero in all other years. We also estimate an alternative specification where we allow the effects of the crisis to change over time. Under this specification, the crisis has an immediate impact in 1998, and its impact decays linearly over time. Because the effect of the crisis on non-performing loans lasted many years, we carry forward the crisis effect to subsequent years. The details of this specification are discussed in Online Appendix A.6. Under this approach, we obtain somewhat larger impacts of the crisis, with 13.2% more branches, 7.6% more markets served, and a 11.8 percentage point increase in financial access ten years later had the crisis not occured.

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 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 targeted 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 7.2% more branches and 4.8% 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 7.4 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.

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## *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

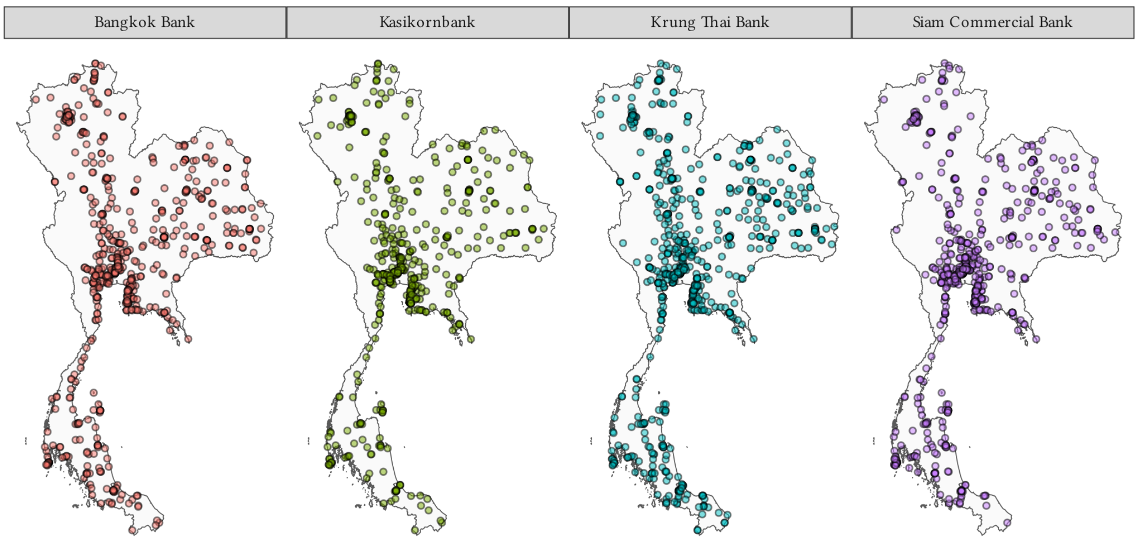
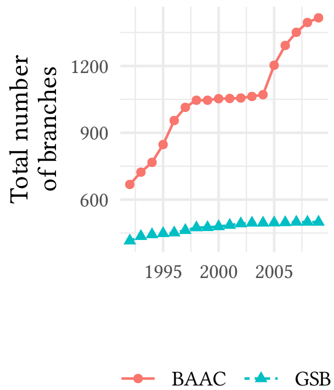
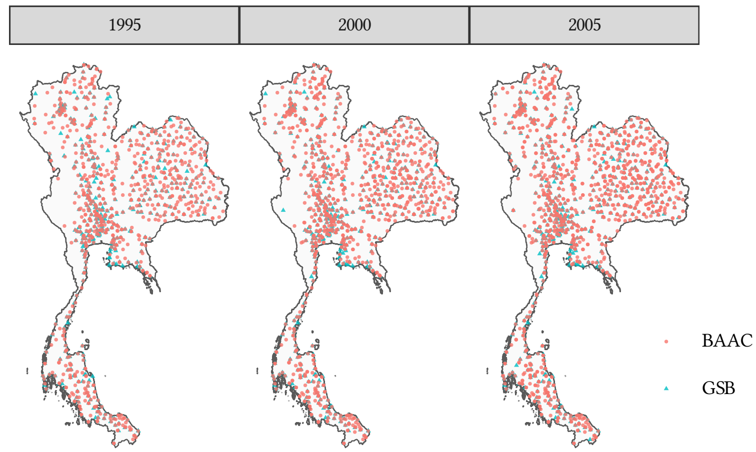



Figure A.1: Locations of all branches ever held by each of the four largest banks.




(A) Total number of BAAC and GSB branches over time.




(B) Locations of BAAC and GSB branches over time.

FIGURE A.2: Evolution of the branch network for government banks.

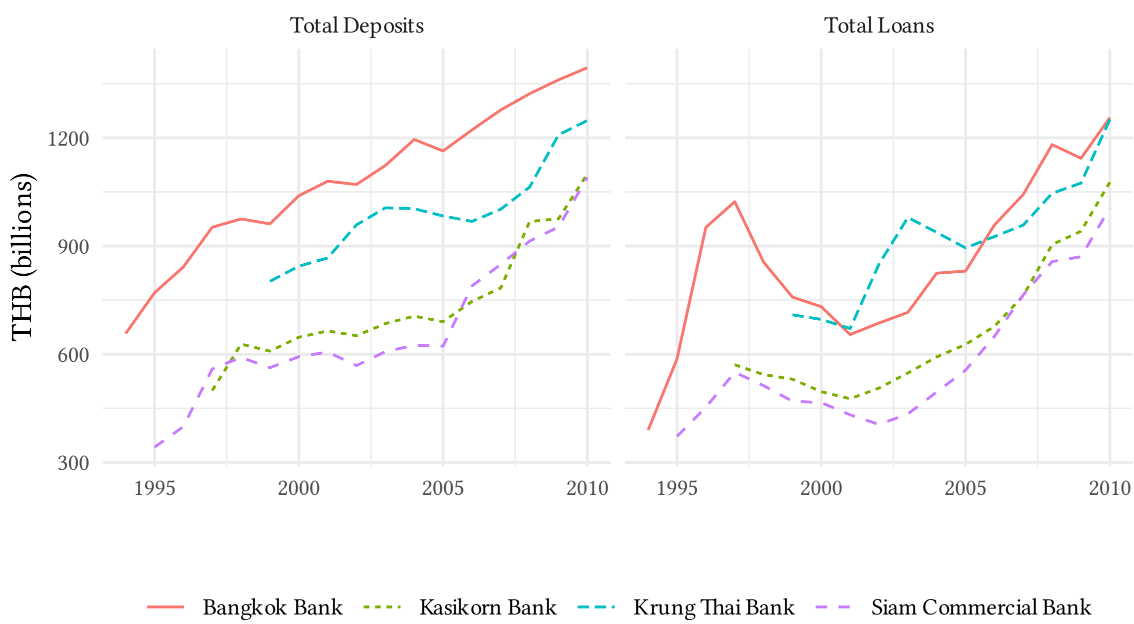



FIGURE A.3: Total loans and deposits from the banks' annaul reports (in billions of Thai Baht).

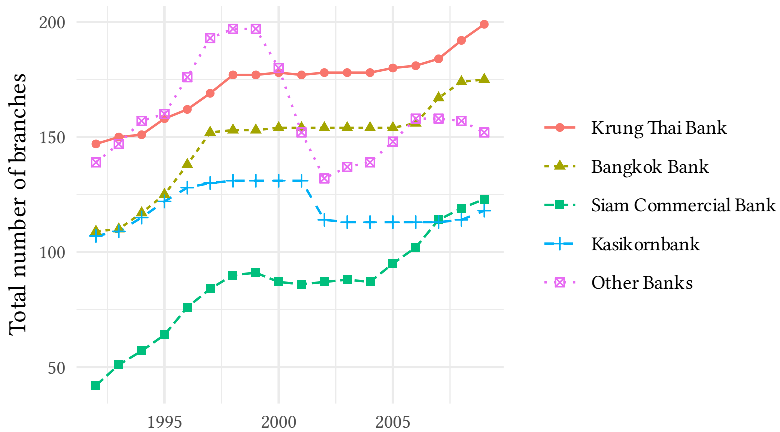



Figure A.4: Total number of branches by bank.

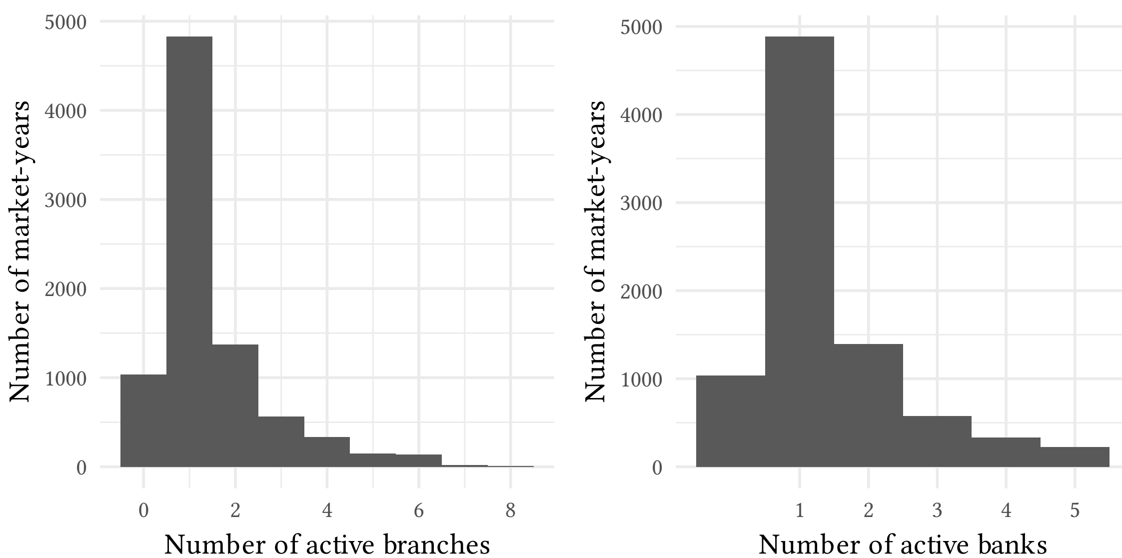
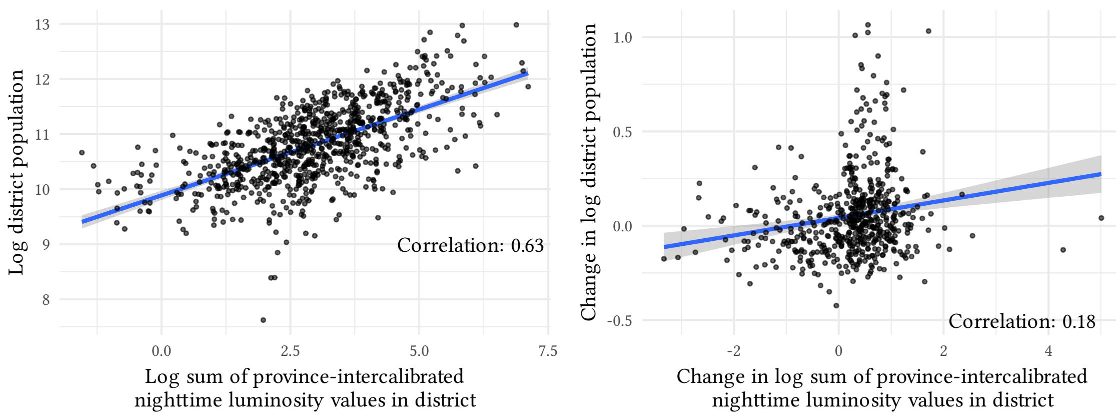



Figure A.5: Number of active branches and active banks in market-years used in estimation.




(A) District-level population in 2000 versus district-level local demand in 2000.

(B) Change in district-level population (2010 vs. 2000) versus change in district-level local demand (2009 vs. 2000).

Figure A.6: Comparing our local demand measure to district-level population data.

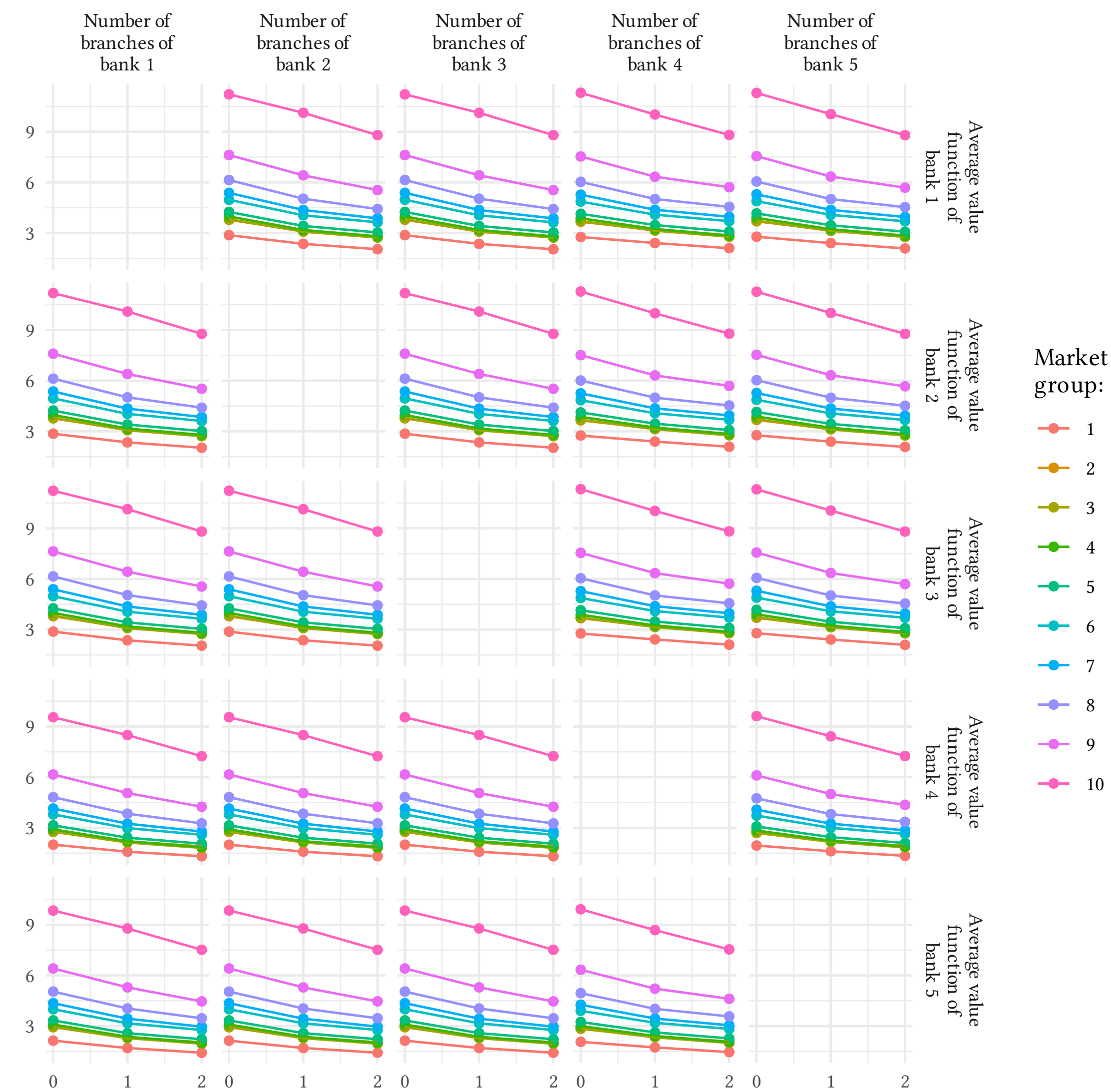
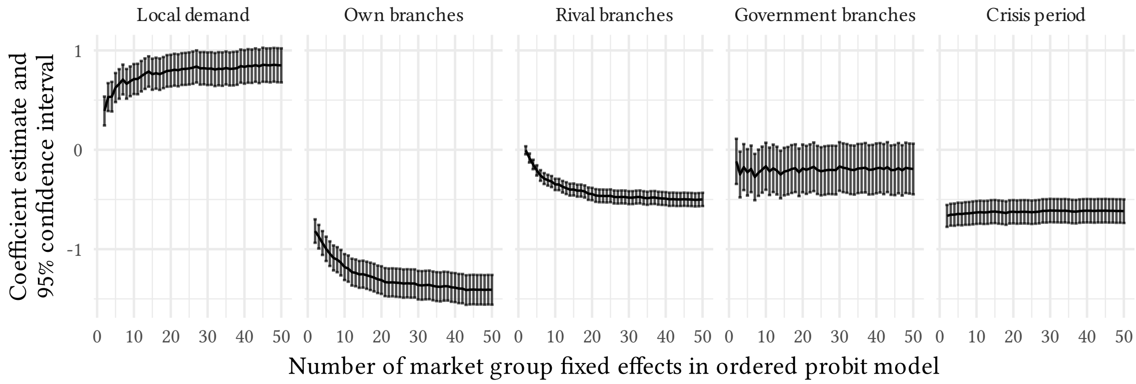
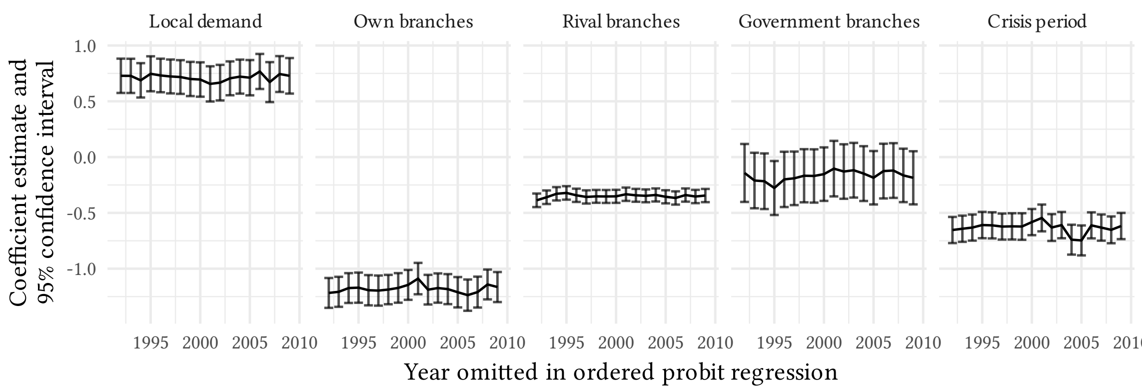



FIGURE A.7: Banks' average value functions as a function of the number of rival branches, split by market group.




Coefficient estimates from an ordered probit regression model with a dependent variable according to entered= +1, do nothing= 0, exited= −1 and a differing number of market group fixed effects. The model additionally includes bank fixed effects. Whiskers represent 95% confidence intervals.

FIGURE A.8: Choosing the number of market groups.




Coefficient estimates from an ordered probit regression model with a dependent variable according to entered= +1, do nothing= 0, exited= −1. The year on the horizontal axis denotes the year dropped from the sample in estimation. The model additionally includes bank fixed effects. Whiskers represent 95% confidence intervals.

FIGURE A.9: Sensitivity of the model to specific years of data.

| *Dependent variable:* | Enter/Nothing/Exit | | |
|---|---|---|---|
| Local demand | 0.712 | 0.710 | 0.710 |
| | (0.077) | (0.077) | (0.077) |
| Own branches | −1.180 | −1.179 | −1.180 |
| | (0.067) | (0.067) | (0.067) |
| Rival branches | −0.348 | −0.348 | −0.348 |
| | (0.029) | (0.029) | (0.029) |
| Government branch presence | −0.166 | −0.165 | −0.165 |
| | (0.121) | (0.121) | (0.121) |
| Crisis period | −0.630 | −0.631 | −0.630 |
| | (0.059) | (0.059) | (0.059) |
| Own branches in other markets within 50km | | −0.394 | |
| | | (0.866) | |
| Own branches in other markets within 100km | | | −0.013 |
| | | | (0.176) |
| Rival branches in other markets within 50km | | 0.070 | |
| | | (0.637) | |
| Rival branches in other markets within 100km | | | −0.017 |
| | | | (0.120) |
| Government branch presence in other markets within 50km | | 0.000 | |
| | | (4.119) | |
| Government branch presence in other markets within 100km | | | 0.379 |
| | | | (4.832) |
| Market group fixed effects | Yes | Yes | Yes |
| Bank fixed effects | Yes | Yes | Yes |
| Number of observations | 42120 | 42120 | 42120 |

Coefficient estimates from an ordered probit regression model with a dependent variable according to entered= +1, do nothing= 0, exited= −1. Standard errors in parentheses.

Table A.1: Sensitivity of including branches from nearby markets.

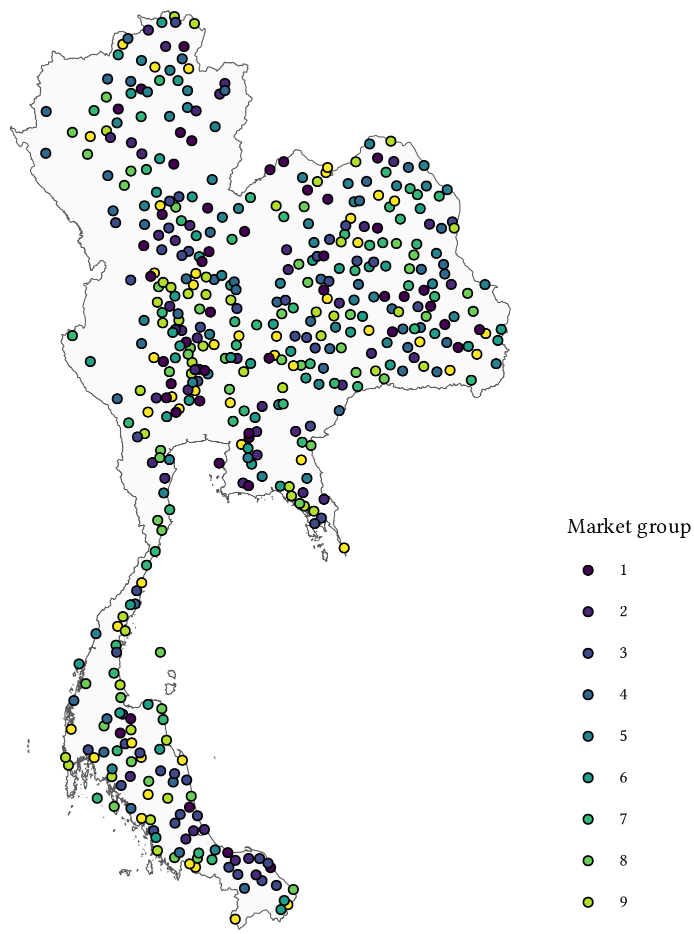
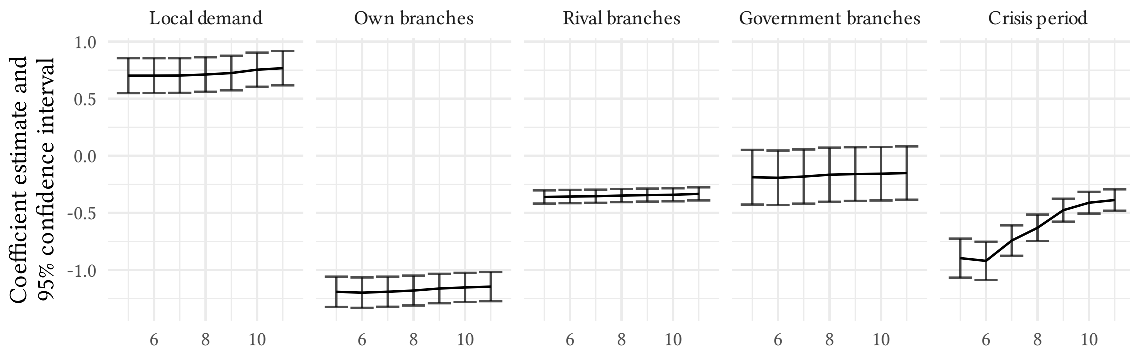
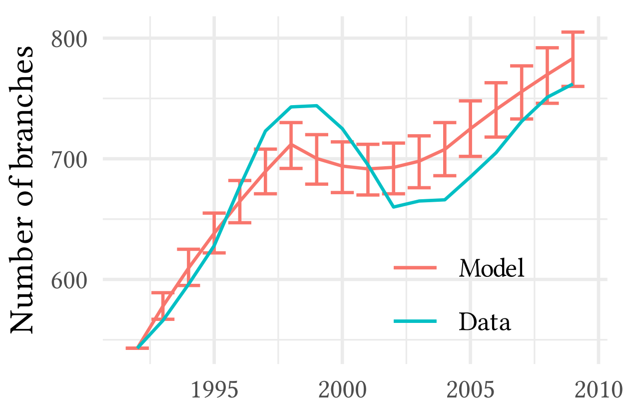



Figure A.10: Geographical distribution of market groups.




Coefficient estimates from an ordered probit regression model with a dependent variable according to entered= +1, do nothing= 0, exited= −1 using different crisis period lengths in estimation. The model additionally includes bank fixed effects. Whiskers represent 95% confidence intervals.

Figure A.11: Sensitivity of the model to crisis period length.




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

Figure A.12: Number of branches by year predicted by model versus data.

| *Dependent variable:* Change in local demand | | |
|---|---|---|
| Market group 1 ($\widehat{\eta}_1$) | 0.010 | (0.003) |
| Market group 2 ($\widehat{\eta}_2$) | 0.010 | (0.003) |
| Market group 3 ($\widehat{\eta}_3$) | 0.002 | (0.003) |
| Market group 4 ($\widehat{\eta}_4$) | −0.002 | (0.003) |
| Market group 5 ($\widehat{\eta}_5$) | 0.001 | (0.003) |
| Market group 6 ($\widehat{\eta}_6$) | 0.005 | (0.003) |
| Market group 7 ($\widehat{\eta}_7$) | −0.001 | (0.003) |
| Market group 8 ($\widehat{\eta}_8$) | −0.001 | (0.003) |
| Market group 9 ($\widehat{\eta}_9$) | 0.000 | (0.003) |
| Market group 10 ($\widehat{\eta}_1 0$) | −0.004 | (0.004) |
| Market group 1 $\times Post_t$ ($\widehat{\eta}_1^{post}$) | −0.008 | (0.003) |
| Market group 2 $\times Post_t$ ($\widehat{\eta}_2^{post}$) | −0.008 | (0.003) |
| Market group 3 $\times Post_t$ ($\widehat{\eta}_3^{post}$) | −0.005 | (0.003) |
| Market group 4 $\times Post_t$ ($\widehat{\eta}_4^{post}$) | −0.007 | (0.003) |
| Market group 5 $\times Post_t$ ($\widehat{\eta}_5^{post}$) | −0.007 | (0.003) |
| Market group 6 $\times Post_t$ ($\widehat{\eta}_6^{post}$) | −0.008 | (0.003) |
| Market group 7 $\times Post_t$ ($\widehat{\eta}_7^{post}$) | −0.005 | (0.003) |
| Market group 8 $\times Post_t$ ($\widehat{\eta}_8^{post}$) | −0.006 | (0.003) |
| Market group 9 $\times Post_t$ ($\widehat{\eta}_9^{post}$) | −0.009 | (0.003) |
| Market group 10 $\times Post_t$ ($\widehat{\eta}_{10}^{post}$) | −0.008 | (0.003) |
| Total number of branches ($\widehat{\alpha}^B$) | 0.002 | (0.001) |
| Government branch presence ($\widehat{\alpha}^G$) | 0.006 | (0.003) |
| 1997 dummy ($\widehat{\delta}_{96}$) | −0.013 | (0.002) |
| 1998 dummy ($\widehat{\delta}_{97}$) | −0.018 | (0.002) |

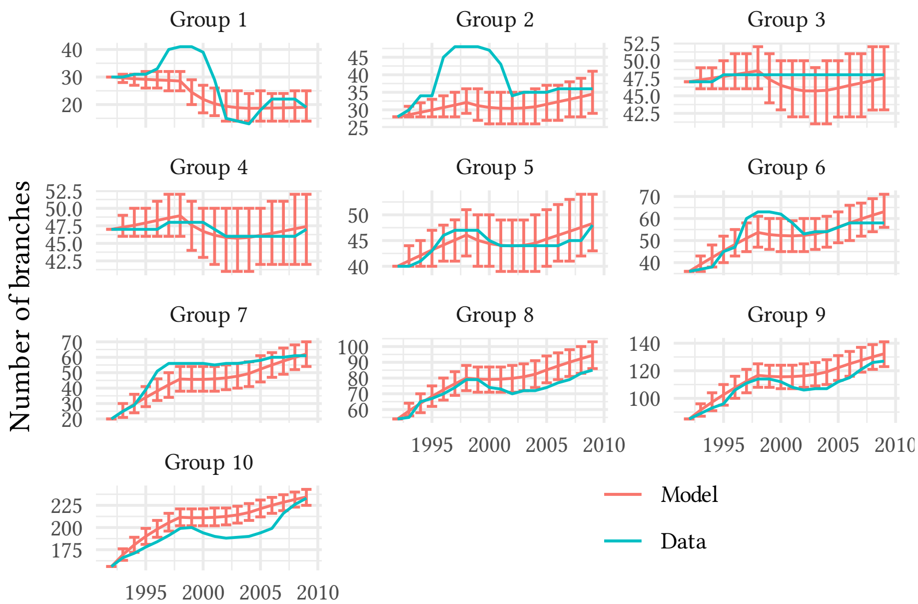
Estimates from a linear regression. Standard errors in parentheses. Local demand is measured using provincial-GDP-intercalibrated nighttime luminosity in a 20km radius around the market centroid.

TABLE A.2: Regression model generating local demand transitions.

| *Dependent variable:* Government branch entry | | |
|---|---|---|
| Intercept | −3.269 | (0.568) |
| Local demand | 56.932 | (16.837) |
| Number of commercial branches | −0.196 | (0.311) |

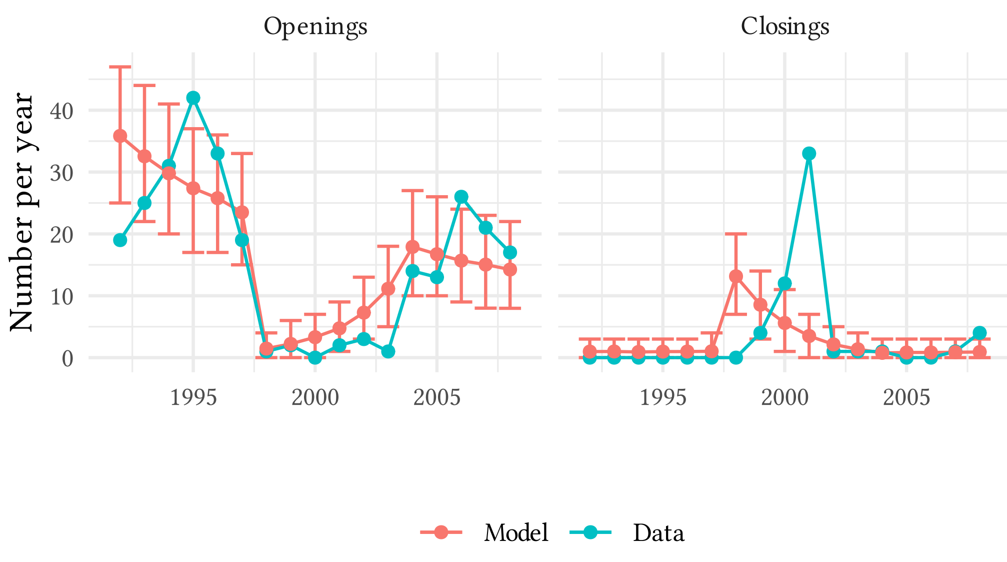
Estimates from a logistic regression. Standard errors in parentheses. Local demand is measured using provincial-GDP-intercalibrated nighttime luminosity in a 20km radius around the market centroid.

TABLE A.3: Logistic regression model generating government bank presence transitions.



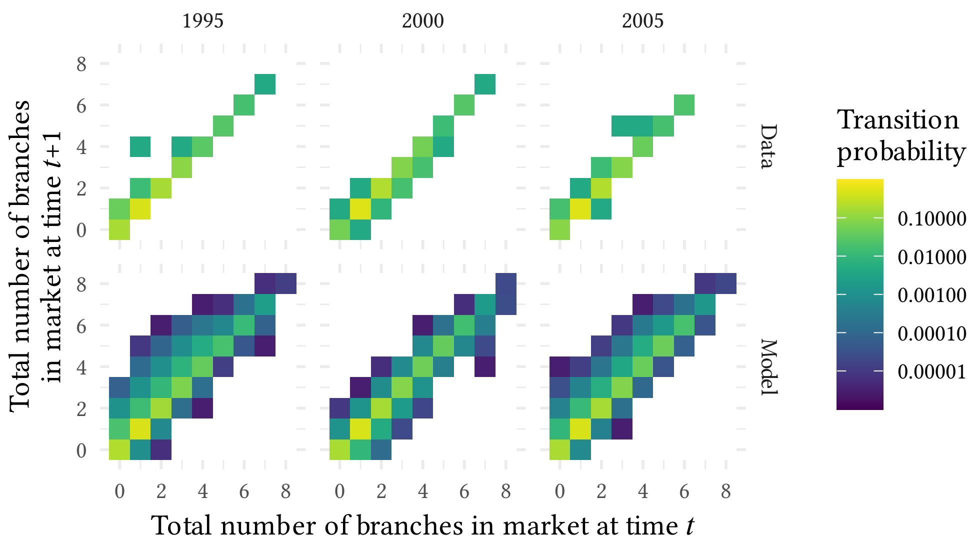

Error bands contain 95% of simulated paths from 1,000 simulations.

FIGURE A.13: Predicted number of active branches versus data by market group.

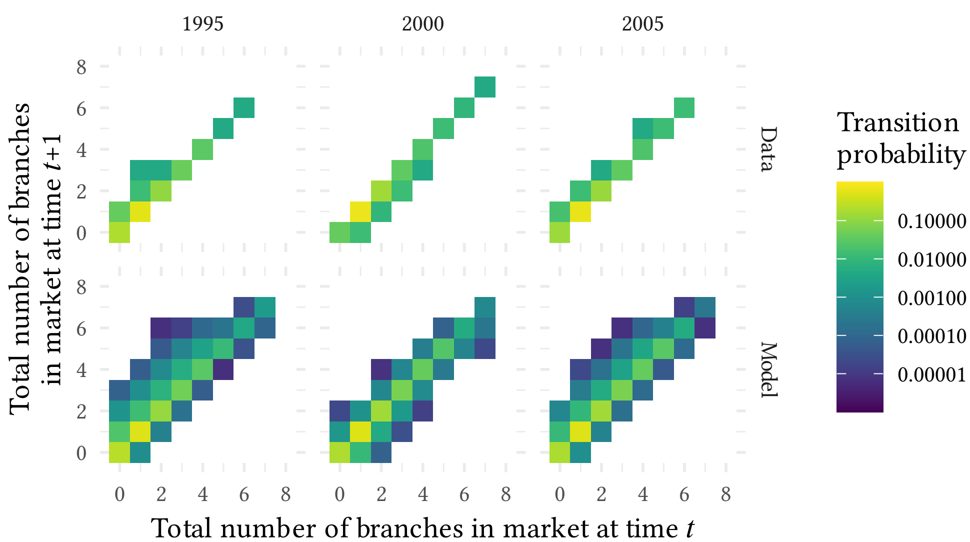



Error bands contain 95% of simulated paths from 1,000 simulations.

FIGURE A.14: Number of openings and closings predicted by model versus data.




(A) Above-median income markets.




(B) Below-median income markets.

FIGURE A.15: Transition probabilities from model and data in 1995, 2000, and 2005 for above- and below-median income markets.

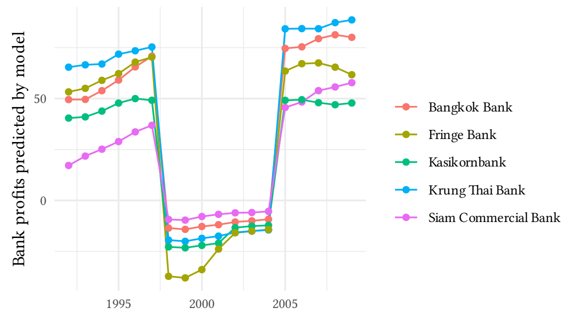



FIGURE A.16: Total annual bank profits predicted by model.

| *Dependent variable:* | Entry probability | |
|---|---|---|
| | (1) | (2) |
| Lost branches | −0.004 | −0.003 |
| | (0.000) | (0.000) |
| Local demand | 0.013 | 0.013 |
| | (0.000) | (0.000) |
| Number of own branches | −0.020 | −0.020 |
| | (0.000) | (0.000) |
| Number of rival branches | −0.011 | −0.011 |
| | (0.000) | (0.000) |
| Government branch presence | 0.002 | 0.003 |
| | (0.000) | (0.000) |
| Crisis period | −0.006 | |
| | (0.000) | |
| Bank fixed effects | Yes | Yes |
| Market group fixed effects | Yes | Yes |
| Year fixed effects | No | Yes |
| Mean of dependent variable | 0.007 | 0.007 |
| Observations | 42120 | 42120 |

Robust standard errors in parentheses. The variable "Lost branches" is an indicator for whether the market has fewer than its past peak number of branches.

TABLE A.4: The effect of losing branches on the entry probability.

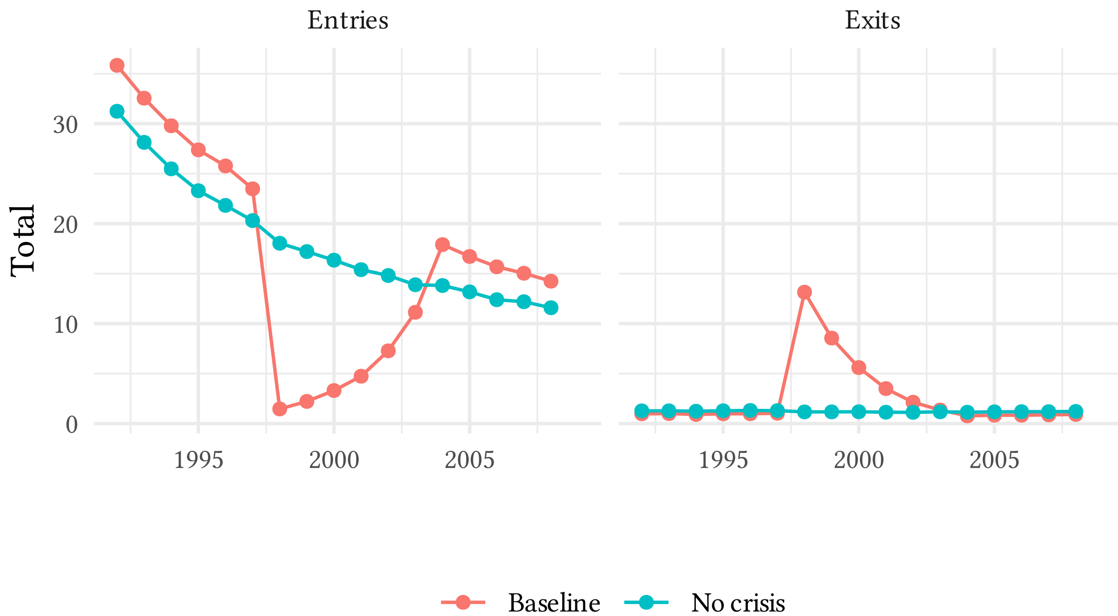
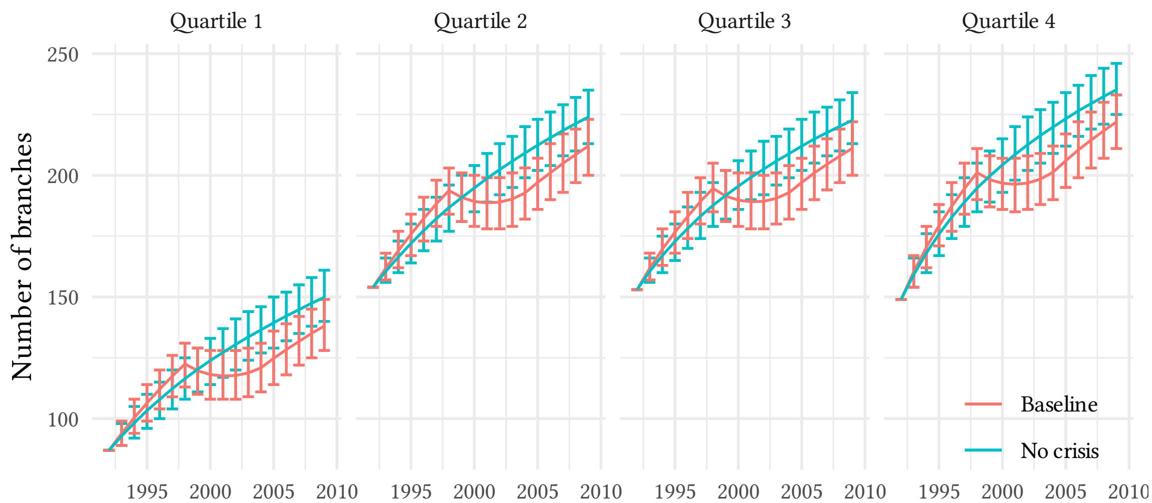
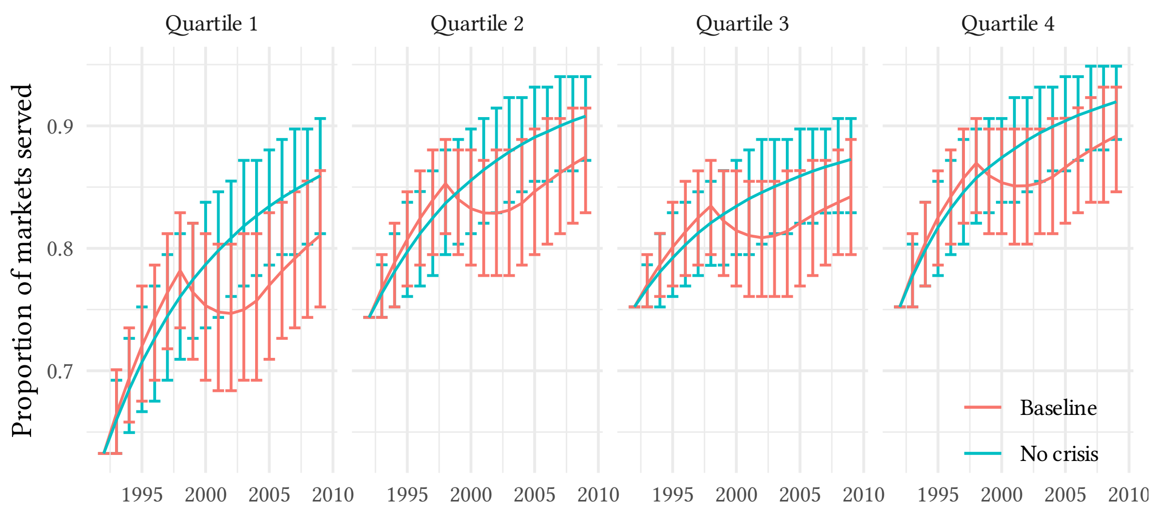



FIGURE A.17: Total number of openings and closures, no crash scenario versus baseline.

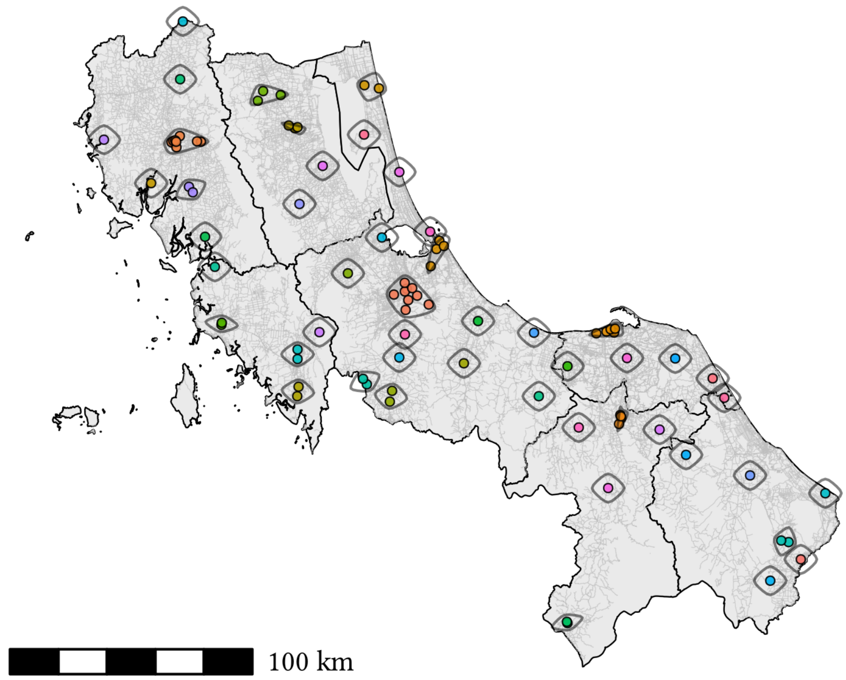



(A) Number of active branches.

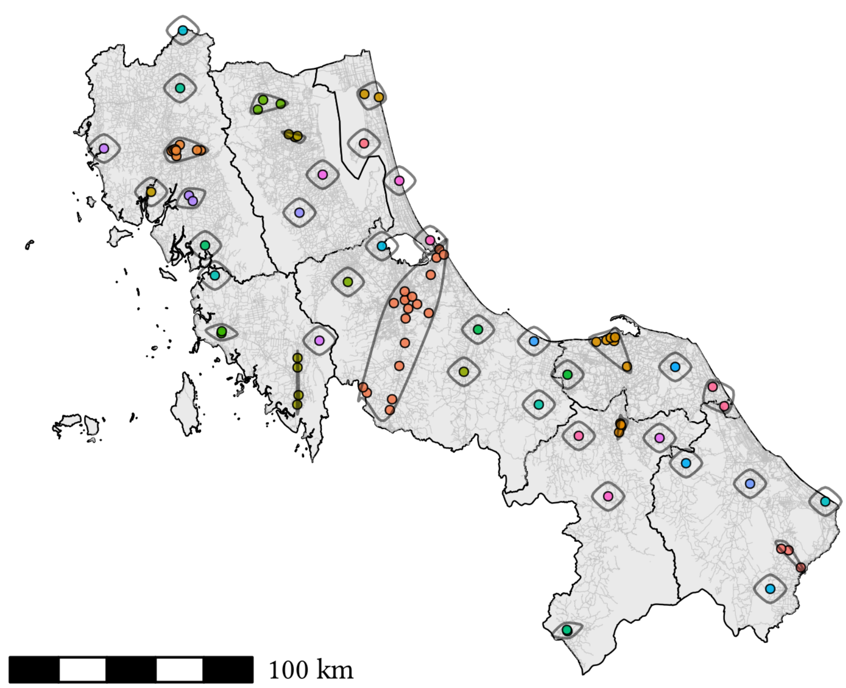



(B) Proportion of served markets.

FIGURE A.18: No crash scenario versus baseline split by income quartiles.




(A) 10km threshold.




(B) 15km threshold.

FIGURE A.19: Clustering locations under a 10km and 15km radius in Southern Thailand.

| | *Distance Threshold* | |
|---|---|---|
| | 10km | 15km |
| Entry cost | 11.749 | 11.355 |
| | (9.735) | (8.970) |
| Local demand | −0.053 | −0.055 |
| | (137.370) | (123.052) |
| Own branches | 0.475 | 0.274 |
| | (44.223) | (49.811) |
| Rival branches | −0.126 | −0.123 |
| | (200.560) | (207.580) |
| Government branch presence | −0.104 | −0.116 |
| | (387.457) | (373.777) |
| Crisis | 0.000 | 0.035 |
| | (205.018) | (187.893) |
| Market group 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 | 7.22 | 7.56 |
| Percentage change in markets served | 4.76 | 4.84 |
| Percentage change in average distance to nearest branch | −29.08 | −30.42 |
| Percentage point change in financial access | 7.39 | 7.80 |

Standard errors in parentheses.

Table A.5: Structural parameter estimates under a 15km distance thresholds to construct markets clusters versus 10km.

| | Banks do internalize effect on growth | Banks do not internalize effect on growth |
|---|---|---|
| Entry cost | 11.749 | 11.729 |
| | (0.314) | (0.312) |
| Local demand | 0.475 | 0.470 |
| | (0.054) | (0.058) |
| Own branches | −0.126 | −0.123 |
| | (0.009) | (0.009) |
| Rival branches | −0.104 | −0.099 |
| | (0.009) | (0.008) |
| Government branch presence | 0.000 | 0.020 |
| | (0.087) | (0.098) |
| Crisis | −0.549 | −0.549 |
| | (0.080) | (0.079) |
| Market group 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 | 7.22 | 7.86 |
| Percentage change in markets served | 4.76 | 4.88 |
| Percentage change in average distance | −29.08 | −30.59 |
| Percentage point change in financial access | 7.39 | 7.85 |

TABLE A.6: Structural estimates when branches do and do not internalize their effect on growth.

| | Baseline specification | Scaled down branch effect on growth |
|---|---|---|
| Entry cost | 11.749 | 11.738 |
| | (0.314) | (0.311) |
| Local demand | 0.475 | 0.449 |
| | (0.054) | (0.058) |
| Own branches | −0.126 | −0.124 |
| | (0.009) | (0.009) |
| Rival branches | −0.104 | −0.100 |
| | (0.009) | (0.008) |
| Government branch presence | 0.000 | 0.035 |
| | (0.087) | (0.079) |
| Crisis | −0.549 | −0.545 |
| | (0.080) | (0.079) |
| Market group 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 | 7.22 | 7.48 |
| Percentage change in markets served | 4.76 | 4.98 |
| Percentage change in average distance | −29.08 | −29.42 |
| Percentage point change in financial access | 7.39 | 7.49 |

TABLE A.7: Structural estimates when scaling down $\widehat{\alpha}^B$ and $\widehat{\alpha}^G$ in equation (10) to half their estimated size.

| | Banks compete | Banks coordinate |
|---|---|---|
| Entry cost | 11.749 | 9.416 |
| | (0.314) | (0.315) |
| Local demand | 0.475 | 0.536 |
| | (0.054) | (0.096) |
| Own branches | −0.126 | −0.094 |
| | (0.009) | (0.007) |
| Rival branches | −0.104 | |
| | (0.009) | |
| Government branch presence | 0.000 | −0.216 |
| | (0.087) | (0.097) |
| Crisis | −0.549 | −0.517 |
| | (0.080) | (0.081) |
| Market group 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 | 7.22 | 6.89 |
| Percentage change in markets served | 4.76 | 4.51 |
| Percentage change in average distance | −29.08 | −28.79 |
| Percentage point change in financial access | 7.39 | 7.30 |

TABLE A.8: Structural estimates when assuming that the banks behave as a cartel.

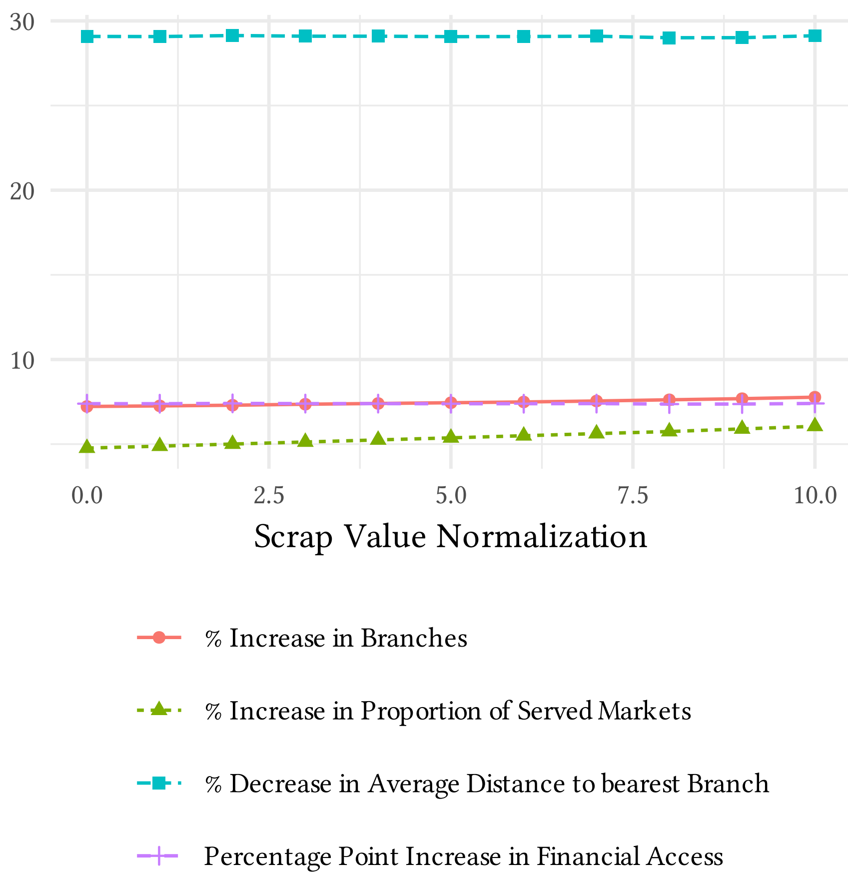



FIGURE A.20: No-crisis counterfactual results under alternative scrap value normalizations.

| | Baseline specification | Scrap value of 1 |
|---|---|---|
| Entry cost | 11.749 | 12.611 |
| | (0.314) | (0.315) |
| Local demand | 0.475 | 0.462 |
| | (0.054) | (0.054) |
| Own branches | −0.126 | −0.126 |
| | (0.009) | (0.009) |
| Rival branches | −0.104 | −0.102 |
| | (0.009) | (0.009) |
| Government branch presence | 0.000 | −0.030 |
| | (0.087) | (0.088) |
| Crisis | −0.549 | −0.523 |
| | (0.080) | (0.080) |
| Market group 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 | 7.22 | 7.17 |
| Percentage change in markets served | 4.76 | 4.68 |
| Percentage change in average distance | −29.08 | −28.38 |
| Percentage point change in financial access | 7.39 | 7.18 |

TABLE A.9: Structural estimates with the scrap value normalized to 1.

## 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 5 banks (0, 1 or 2) and whether or not a government branch is present. We therefore solve the value function at $10 \times 3^5 \times 2 = 4,860$ points separately for each time period and each of the 10 market groups. 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 $\widehat{z}_{k(m),\tau+1}\left(z_{m\tau}, \sum_{f=1}^{F} n_{fm\tau}, g_{m\tau}\right)$ denote the predicted value from the estimated transition process for local demand in time period $\tau+1$, market group $k$, with a current value of local demand $z_{m\tau}$, $\sum_{f=1}^{F} n_{fm\tau}$ active branches and indicator for government branch presence $g_{m\tau}$. 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 group $k$ at time $\tau$ given $\sum_{f=1}^{F} n_{fm\tau}$ branches and government branch presence $g_{m\tau}$ is then given by:

$$\Pr\left(\widetilde{z}_j \,\middle|\, \widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}, g_{m\tau}, k(m), \tau\right) =$$
$$\begin{cases} \Phi\left(\frac{-\widehat{z}_{k(m),\tau+1}\left(\widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}, g_{m\tau}\right)}{\widehat{\sigma}_\nu}\right) & \text{if } j = 1 \\ 1 - \Phi\left(\frac{\widetilde{z}_{10} - \widehat{z}_{k(m),\tau+1}\left(\widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}, g_{m\tau}\right)}{\widehat{\sigma}_\nu}\right) & \text{if } j = 10 \\ \Phi\left(\frac{\underline{z}_j - \widehat{z}_{k(m),\tau+1}\left(\widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}, g_{m\tau}\right)}{\widehat{\sigma}_\nu}\right) - \Phi\left(\frac{\underline{z}_{j-1} - \widehat{z}_{k(m),\tau+1}\left(\widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}, g_{m\tau}\right)}{\widehat{\sigma}_\nu}\right) & \text{otherwise} \end{cases} \tag{15}$$

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 4,860 points for each time period and market group. 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 $a = 0$ and zero otherwise. That is, the first guess assumes all banks do not open or close any branches in all states.[38] 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 $\Pr\left(\widetilde{z}_j \middle| \widetilde{z}_i, \sum_{f=1}^{F} n_{fm\tau}, k\left(m\right), \tau\right)$ in equation (15).

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.[39] 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:

$$\max_{\substack{f\in\{1,\ldots,F\},\\ \boldsymbol{s}_{mt}\in\widetilde{\mathcal{S}},\\ a\in\mathcal{A}\left(n_{fmt}\right)}} \left|p_f^j\left(a_{fmt} = a|\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right) - p_f^{j-1}\left(a_{fmt} = a|\boldsymbol{s}_{mt}, \boldsymbol{\theta}\right)\right| < 1 \times 10^{-9} \tag{16}$$

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 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. Because the equilibrium strategies will be the same for all markets of the same market group, we can solve for the equilibrium once for each group instead of each market, which allows for computation in parallel over all

[38]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.

[39]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.

10 market groups.

## A.3 The Estimated Cost of Entry

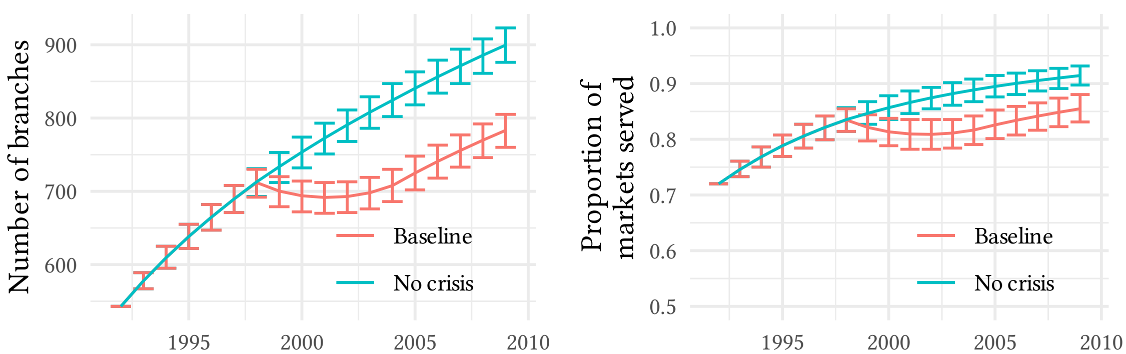
Our estimated entry cost is 25.46 times the average branch profits in 2005. We do not view this number as unrealistically large. If flow profits are held fixed and the annual discount rate is $\beta = 0.95$, the present discounted value of the stream of flow profits is $\beta/(1-\beta) = 19$ times the flow profits. With an entry cost at 25.46 times the flow profit, firms are unlikely to enter in average markets. But even then, holding fixed the average branch profits of 0.461, a bank would open a branch if $19 \times 0.461 - \theta^{ec} + \varepsilon^{1}_{fmt} > \varepsilon^{0}_{fmt}$, which occurs with probability 0.048 under our distributional assumptions. Therefore entry still takes place with some frequency. Furthermore, the entry cost is only 17.77 times the annual flow profits for branches in the 90th percentile of flow profits, and only 12.4 times the flow profits for monopolist branches in market group 10 at the average level of local demand. This makes entry much more likely in high-demand markets. In addition, firms expect local demand to grow, not stay fixed, which makes the value of entering larger than 19 times the current flow profits, particularly before the crisis. Such a large estimated entry cost is also not uncommon in this literature. Igami and Yang (2016) estimate the sunk cost of entry for McDonald's to be 7.96, 9.24 and 72.0 times the base flow profit for each of their three market types and Lin (2015) estimate the the sunk cost of entry to be 9-12 times the monopolist profits.

In our estimation, we assume the action-specific private information shocks $\boldsymbol{\varepsilon}_{fmt}$ are distributed standard Type I extreme value (Gumbel). As is typical, the variance of these shocks is normalized to $\frac{\pi^2}{6}$ as it is not separately identified from the parameters determining the flow payoffs (Train, 2009). An alternative normalization for this variance would scale the other parameters. If one of the parameter values were known ex ante, this could be fixed and the variance of the private information shocks could be estimated. However, in our setting none of the parameter values are known.

Finally, we argue that the entry cost cannot be given a monetary interpretation. This is because the size of the entry cost depends on a number of researcher-chosen values, such as the number of potential markets, the maximum possible number of branches, the number of potential entrants, and the discount factor. For example, adding additional potential markets or entrants decreases the observed rate of entry, which would lead to a larger estimated entry cost. Therefore we cannot interpret the scale of the entry cost in monetary terms.

## A.4 The Effects of the Crisis if Pre-Crisis Growth Continued

We perform an additional counterfactual experiment to simulate branching decisions under alternative assumptions for the no-crisis scenario. In this case, we assume the crisis indicator $\zeta_t$ is equal to zero in all time periods and the transition process of local demand follows the pre-crisis process shown in equation (11) in all periods. The results from this counterfactual experiment are plotted in Figure A.21. We can see that both the number of branches and proportion of served markets are the same until 1997, after which the counterfactual shows these continuing according to their pre-crisis trend. By 2007, ten years after the crisis, there are 15.3% more branches, and 7.6% more markets served, which is larger compared to our baseline counterfactual. The average distance to the nearest branch falls by 44.6%, and financial accress increases by 12.7 percentage points.




(A) Number of active branches.

(B) Proportion of served markets.

FIGURE A.21: Branch network expansion under no crash versus baseline, assuming pre-crisis growth continues post crisis.

## A.5 Decomposition of Crisis Effects

There are two primary components of our model that change during the crisis that can slow down branch openings and lead to closures: the crisis indicator $\zeta_t$ is activated which lowers profits, and the local demand transition process changes. The local demand transition process changes in both levels and growth rates: the $\delta_{96}$ and $\delta_{97}$ terms in equation (10)

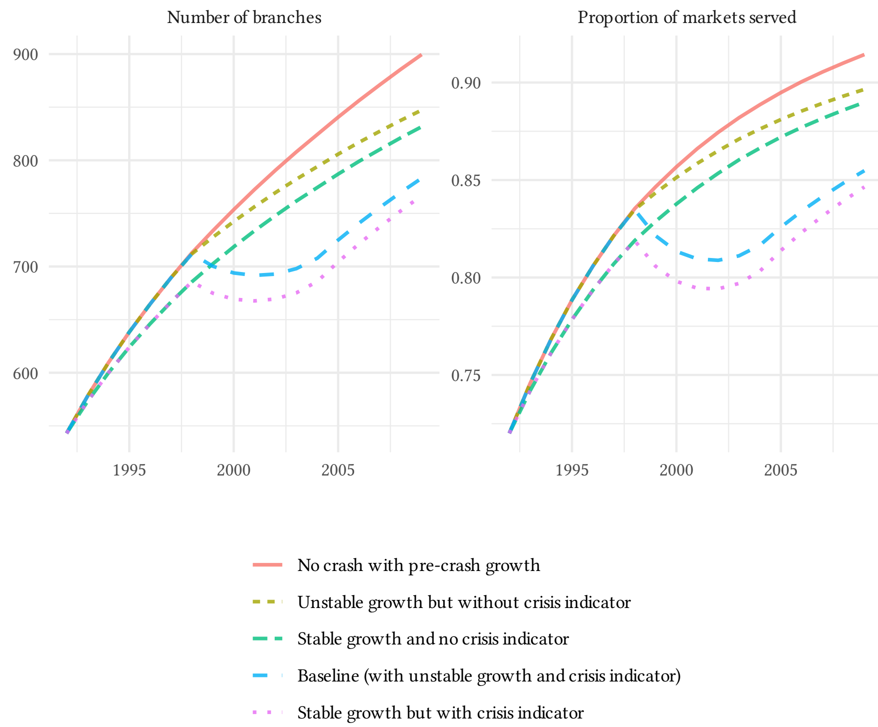



FIGURE A.22: Decomposition of crisis effects.

immediately decrease local demand, and the $\eta^{post}_{k(m)}$ terms decrease the growth rate. We decompose the effect of each of these terms by running separate counterfactual experiments where we activate one and not the other. The results of these experiments are down in Figure A.22, which shows the total number of branches and proportion of markets served in our sample period. Because we overlay several experiments, we omit error bands to maintain legibility.

The top line shows the outcome from setting $\zeta_t = 0$ in all time periods and setting local demand to follow the pre-crisis process in all periods. This is the same as Figure A.21 discussed in Online Appendix A.4. Here, branching continues according to the pre-crisis trend after the crisis. The next line shows the outcome from growth following the unstable process as estimated from the data, but the crisis indicator $\zeta_t$ is equal to zero in all time periods. Here, there is no net exit from the crisis, but entry slows compared to the first scenario. The next scenario is when $\zeta_t = 0$ in all time periods and growth is stabilized with $\eta^{\star}_{k(m)}$ in all time periods. This corresponds to the results in Figure 11. Here, the total number of branches at the end of our sample period is lower compared to the more volatile growth scenario, as the high growth before the crisis enouraged considerable entry in the market. The next scenario corresponds to the baseline case where the crash occurs: the crisis indicator is activated during the crisis and growth in local demand is unstable. Finally, the last scenario is when the crisis indicator is activated during the crisis and growth is stabilized with $\eta^{\star}_{k(m)}$ in all time periods. This scenario results in the lowest number of branches and proportion of served markets by the end of the sample period.

## A.6 Allowing the Crisis Terms to Vary Over Time

In our baseline specification, the crisis indicator reduces profits by $\theta^{crisis}\zeta_t$ for the crisis years. We now compare our results to an alternative specification where we allow the effect of the crisis to vary over time. We define the following alternative crisis term:

$$\widetilde{\zeta}_t\left(\theta^{crisis,0},\theta^{crisis,t}\right)=\begin{cases}\theta^{crisis,0}+\theta^{crisis,t}\left(t-1998\right) & \text{if } t\geq 1998\\ 0 & \text{otherwise}\end{cases}$$

Here, $\theta^{crisis,0}$ is the immediate effect of the crisis, and $\theta^{crisis,t}$ is how the crisis changes over time. If $\theta^{crisis,0}<0$ and $\theta^{crisis,t}>0$ (as we estimate), the crisis has an immediate negative effect on profits and decays over time. Because the effects of the crisis persisted for many years after 1997, we assume that banks experience to cumulative sum of the $\widetilde{\zeta}_t\left(\theta^{crisis,0},\theta^{crisis,t}\right)$ terms since the start of the crisis, until its impact is zero. Thus, the term replacing $\theta^{crisis}\zeta_t$ in the profit function is given by:

$$\max\left\{\sum_{\tau=1998}^{t}\widetilde{\zeta}_\tau\left(\theta^{crisis,0},\theta^{crisis,t}\right),0\right\}$$

Under this specification, we do not need to assume how many periods the crisis will last. This will be determined by the size of the estimates of $\theta^{crisis,0}$ and $\theta^{crisis,t}$. We use the same assumptions regarding banks' beliefs under this specification: Before the crisis arrives, banks believe $\widetilde{\zeta}_t\left(\theta^{crisis,0},\theta^{crisis,t}\right)=0$ forever, and after the crisis arrives banks learn the true process.

The estimates under this specification are shown in Table A.10. Apart from the crisis terms, the estimates are similar to our baseline specification. Based on the estimated parameters, the term $\widetilde{\zeta}_t\left(\theta^{crisis,0},\theta^{crisis,t}\right)$ is negative for 6 time periods. However, the negative

| | Estimate | Standard Error |
|---|---|---|
| Entry cost | 12.006 | (0.320) |
| Market group 1 | 0.180 | (0.091) |
| Market group 2 | 0.278 | (0.091) |
| Market group 3 | 0.313 | (0.098) |
| Market group 4 | 0.350 | (0.110) |
| Market group 5 | 0.363 | (0.093) |
| Market group 6 | 0.407 | (0.093) |
| Market group 7 | 0.462 | (0.089) |
| Market group 8 | 0.523 | (0.090) |
| Market group 9 | 0.636 | (0.096) |
| Market group 10 | 0.920 | (0.104) |
| Bank 2 | 0.000 | (0.011) |
| Bank 3 | 0.003 | (0.011) |
| Bank 4 | −0.066 | (0.013) |
| Bank 5 | −0.052 | (0.011) |
| Local demand | 0.456 | (0.055) |
| Own branches | −0.130 | (0.010) |
| Rival branches | −0.105 | (0.009) |
| Government branches | 0.007 | (0.088) |
| Crisis constant | −0.172 | (0.032) |
| Crisis trend | 0.033 | (0.008) |

Table A.10: Structural parameter estimates allowing the crisis to vary over time.

impact on profits persists for 11 periods, with the peak occurring during 2001-2003, the years we observe banks closing the most branches. This can also be seen in Figure A.23 where we show the predicted bank profits from using this specification of the model. We can see that profits are lowest over 2001-2003.

Using these estimates, we repeat our counterfactual experiment simulating branching under a no-crisis scenario. Again, we solve for the $\eta^{\star}_{k(m)}$ that result in the same local demand in our last time period as the baseline case, and set $\widetilde{\zeta}_t\left(\theta^{crisis,0}, \theta^{crisis,t}\right) = 0$ in all time periods. The results are shown in Figure A.24. Here, we obtain somewhat larger impacts of the crisis, with 13.2% more branches, 7.6% more markets served, and a 11.8 percentage point increase in financial access ten years later.

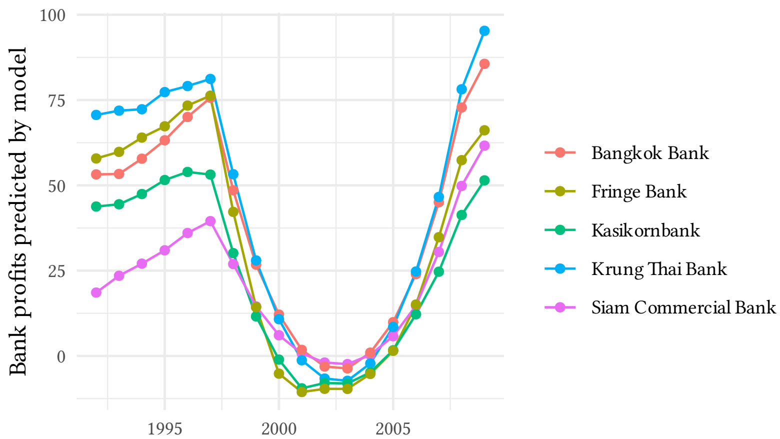
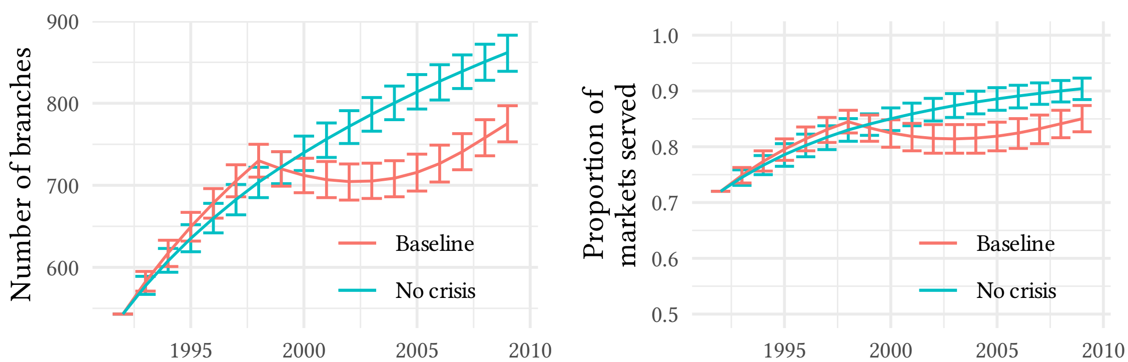



FIGURE A.23: Total annual bank profits predicted by model with a flexible crisis term.




(A) Number of active branches.

(B) Proportion of served markets.

FIGURE A.24: No crash scenario versus baseline scenario with a flexible crisis term.

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