

Dynamic Bank Expansion: Spatial Growth, Financial Access, and Inequality

Yan Ji Songyuan Teng Robert M. Townsend

November 6, 2022

Abstract

We propose a model with local spatial markets and heterogeneous agents to understand and evaluate the geographic expansion of bank branches after banking deregulation in Thailand. The model features heterogeneity in financial frictions across regions, with the costs of accessing credit and deposits depending on the distance from the nearest branch. Disciplined by micro estimates of the effects of branch openings, the model reproduces salient regional and aggregate patterns concerning occupational choice, financial access, and inequality. We apply the model to study two counterfactual financial sector policies in distant markets, one subsidizing branches and the other subsidizing household deposits.

JEL codes: C54, E23, E44, F43, O11, O16, R11, R13

Keywords: financial inclusion, spatial equilibrium, regional heterogeneity, growth and inequality, transitional dynamics

The Online Appendix of this paper can be found at [this link](#)

*Ji: Department of Finance, Hong Kong University of Science and Technology (email: jiy@ust.hk); Teng: Department of Economics, Yale University (email: songyuan.teng@yale.edu); Townsend: Department of Economics, MIT (email: rtownsen@mit.edu). This paper was previously circulated under the title “Branch expansion versus digital banking: the dynamics of growth and inequality in a spatial equilibrium model.” We are grateful to the editor and four anonymous referees for their constructive comments. We thank Christian Ahlin, Abhijit Banerjee, Saki Bigio, Emilio Bisetti, Ariel Burstein, Dean Corbae, Vidhan Goyal, Alex Xi He, Hugo Hopenhayn, Greg Kaplan, Kai Li, Xiao Ma, Abhiroop Mukherjee, Yoshio Nozawa, Xiao Zhao, and Fabrizio Zilibotti for helpful discussions. We also thank seminar and conference participants at MIT, Michigan State University, UCLA, HKUST, CUF, Workshop on Finance and Development, Society for the Advancement of Economic Theory (SAET), Roundtable on Central Banking and Inequality, North American Summer Meeting of the Econometric Society, Asian Meeting of the Econometric Society, Society for Economic Dynamics, Australian Meeting of the Econometric Society, and China International Conference in Macroeconomics for their comments and suggestions. Yan Ji is grateful for the financial support of the Hong Kong RGC GRF Grant (Project No. 16500718). Townsend gratefully acknowledges research support from Eunice Kennedy Shriver National Institute of Child Health and Human Development (NICHD) (grant number R01 HD027638), the Centre for Economic Policy Research (CEPR), and the Department for International Development (DFID) under grant MRG002_1255.

1 Introduction

Implementing financial sector policies that promote financial inclusion and growth is one of the key goals of developing economies. Often, these policies generate spatially uneven impacts. Some selectively target certain regions; for example, reforms in China during the 1970s focused on advancing the capital market in the eastern coastal provinces, and some developing countries have implemented policies to promote deposit mobilization in rural areas. Some policies do not focus on specific regions, but the endogenous reactions of financial institutions generate spatially different outcomes. For example, branching deregulation results in a geographic expansion of the branch network. Understanding the economic impacts of such policies across space and over time is crucial. Today, even developed countries such as the U.S. remain concerned about income inequality and equitable financial access in local markets.¹

This paper develops a spatial equilibrium model with heterogeneous agents to evaluate the dynamic expansion of bank branches in Thailand for the 1986-1996 period. Due to a relaxation of branching requirements in the late 1980s, amid other financial reforms, the Thai economy experienced unprecedented growth in the number of bank branches during this period. We take the overall number of new branches as given in our model and focus on predicting the locations of these branches and their impacts. Our model is not particular to Thailand, as our objective is to provide a micro-founded macroeconomic framework to quantitatively explore the links across both space and time, which can be applied to many countries.

Through the lens of the model, we provide three sets of quantitative results. First, our model correctly predicts most branch locations in the data, providing a structural interpretation of how they could be rationalized by profit maximization over regions that display spatial heterogeneity. Second, using a difference-in-differences (DID) approach, we empirically estimate that branch openings significantly increase a local market's income, employment, credit access, and firm entry. By disciplining and validating the model with these micro estimates, we shed light on the aggregate and distributional implications of bank expansion through the underlying credit and deposit channels. Third, we use the model to study two counterfactual financial sector policies, one that subsidizes household savings and one that subsidizes branch profits; both are applied in distant markets and have the same overall cost. We show that both policies can help mobilize rural deposits because of their impacts on endogenous branch locations, but, they have the opposite implications for income inequality.

Below, we elaborate on the main results of this paper. Before 1986, commercial banks in

¹In the U.S., about 30% of the poor are unbanked (C  lerier and Matray, 2019). The ConnectALL initiative launched in 2016 aimed to help Americans to access the Internet and benefit from safe and affordable online payment, borrowing, and savings products. In early 2019, a survey by the Pew Research Center found that 26% of adults living in households earning less than \$30,000 a year did not have broadband Internet at home (Furman, 2016).

Thailand were required to hold a significant proportion of low-return government bonds to expand. To liberalize bank branching, the Thai government gradually lifted the bond-holding requirement in the late 1980s, which effectively lowered the costs of setting up new branches. In response to this banking deregulation, the number of commercial bank branches more than doubled from 1986 to 1996.

Using detailed geographic information system (GIS) data, we construct over 1,000 local spatial markets for the Thai economy based on the locations of marketplaces and the transportation network. We estimate the impacts of branch openings in these local markets by exploiting variations in branch locations and the timing of their establishment in a DID framework with staggered treatment. We use propensity score matching to improve the comparability between the treatment and control markets. Our empirical estimates indicate that bank expansion has significant effects on local markets' income, employment, credit access, and firm entry.

We develop a structural economic model to interpret the micro estimates and deepen our understanding of the expansion of bank branches. Our model is essentially a growth model with financial frictions (e.g., [Greenwood, Sanchez and Wang, 2010](#); [Buera and Shin, 2013](#); [Midrigan and Xu, 2014](#)) that is extended to incorporate local spatial markets. We introduce ingredients which are novel in their combination. First, we model not only the costs of credit access but also the costs of portfolio adjustment for cash and deposits, which, analogous to the liquid and illiquid assets emphasized by [Kaplan and Violante \(2014\)](#), differ in their liquidity.² Second, these costs differ across markets as a function of how close each market is to the nearest bank branch, which is endogenous in the model.

In our model, local spatial markets differ from each other in three dimensions: size, productivity, and distance from the nearest branch. Market size determines a market's contribution to the aggregate economy, productivity determines the production efficiency of local enterprises, and distance from the nearest branch determines the costs of accessing credit and deposits. In addition, our model considers heterogeneous households within each market, allowing us to provide sound microfoundations for regional and aggregate dynamics in household behavior. Households optimally determine their occupations (i.e., farmer, worker, or entrepreneur), consumption, and holdings of assets (cash and deposits) and loans. They face financial frictions that vary depending on the markets in which they live, and they can choose to migrate to other markets.

The choice of locations for new branches across markets is made by a central authority, which maximizes total intermediation profits as if there is a coordinating profit-maximizing monopoly. Although we make this assumption mainly for tractability, it reflects the highly concentrated commercial banking sector of Thailand and the prevalence of government ownership. Profit maximization implies that branches tend to be opened in populous and productive regions, or in

²The categorization of what is liquid versus illiquid varies with the context. In our study, cash is liquid to make payments, and deposits (i.e., bonds) are illiquid assets.

regions with a cluster of markets that are distant from existing branches, so opening a branch can serve households from multiple nearby markets. New branch openings reduce the costs of accessing credit and deposits for households in immediate and nearby regions, which increases credit access and demand for interest-bearing deposits, capturing the credit and deposit channels of bank expansion, respectively.

We calibrate the three characteristics of local markets using detailed GIS data. Specifically, a local market’s size is calibrated based on population density, and its distance from the nearest branch is calibrated by the car travel time along the road network. A local market’s productivity is calibrated based on the residual value of a cross-sectional regression which captures cross-market differences in income per capita that are not explained by differences in capital stock or access to bank branches. We calibrate the key parameters of the model to match the empirical DID estimates for the 2-year effects of branch openings on local employment and credit access. To ensure the credibility of the calibrated model, we validate that all DID estimates in the model are aligned with those in the data, not only for the two targeted point estimates, but also for the untargeted estimates of the impacts of branch openings on the local fraction of entrepreneurs and income per capita, including all leads and lags.

We first evaluate the calibrated model’s ability to predict branch locations. Among the 431 new branches opened in the 1987-1996 period, our model correctly predicts the locations of 372 branches, representing a correct prediction ratio of 86.3%. The average model-predicted branch opening time is about 2.38 years different from that in the data. As a benchmark, if branch locations were randomly assigned, the correct prediction ratio would drop significantly to 42.2% and the average model-predicted branch opening time would differ by about 7.05 years from that in the data. The model captures the waves of branch openings across regions well, including the major upturns and downturns in new branch openings in the data, despite the fact that they are not targeted in our calibration. Across regions, the model suggests that accounting for the spatial difference in productivity is crucial in explaining the high density of branches around Bangkok and the low density of branches in the northeast of Thailand. Accounting for markets’ distance from existing branches significantly improves the predictive power of the model in the central, north, and northwest regions of Thailand.

Next, we shift the lens of the model from a micro to a macro perspective by combining the market-level effects to evaluate the aggregate implications of bank expansion. Our model suggests that bank expansion largely explains the strong upward trend in the fraction of entrepreneurs and their access to bank loans, the strong downward trend in credit access inequality across markets, and the strong labor transition from farming to wage labor. Further, we zoom in on households across and within markets, tracing the origins of growth and inequality and their trends over space. A salient feature in the data is that the aggregate income Gini coefficient exhibits an

inverted U-shape between 1986 and 1996, consistent with the Kuznets’ hypothesis. Relatedly, the income share of the top decile of the income distribution displays a similar inverted U-shape, whereas the share of the bottom 50% is U-shaped. We find that within-market inequality increases steadily, whereas cross-market income inequality exhibits an inverted U-shape, indicating that the latter drives the shape of overall income inequality during this period. These empirical patterns cannot be easily rationalized by models without spatial heterogeneity.³ By reproducing these patterns, we validate our model and elucidate the potential channels behind them. Specifically, the expansion of branches promotes financial inclusion across markets, which increases income. Initially, branch expansion increases cross-market income inequality because most markets lack branches. However, in later years, as the majority of markets have branches, continued branch expansion leads to lower cross-market income inequality. Furthermore, the model indicates that it is the credit channel that generates the inverted U-shape due to its large impacts on local income, whereas the deposit channel slightly increases cross-market income inequality due to the general equilibrium effect on interest rates.

Constructing normative metrics, our model implies that bank expansion over our study period leads to an overall country-wide welfare increase of about 19.9%, of which 11.4% is attributed to the credit channel, 4.5% to the deposit channel, and the remainder to the complementarity between these two channels. The impacts are heterogeneous; markets distant from branches in 1986 experience welfare gains of more than 50% after the opening of a local branch, whereas welfare changes little for markets with branches in 1986. In addition, within each market, there are significant variations in the welfare implications for households. In the markets in which a new branch opened between 1987 and 1996, large welfare gains are experienced both by talented but wealth-constrained households through the credit channel, and by untalented but wealthy households through the deposit channel. Conversely, in the markets with branches in 1986, the former household group experiences slight welfare losses due to the general equilibrium effect; that is, bank expansion increases the equilibrium interest rate, which increases entrepreneurs’ costs of production and reduces their business income.

Finally, we apply the validated model to study two counterfactual financial sector policies: a policy subsidizing the portfolio adjustment costs of households living in markets distant from existing branches, and a policy subsidizing the profits of branches opened in these markets. We show that both policies are effective in reaching the unbanked population because they induce branch openings in distant markets. Subsidizing households results in a significant increase in the deposit-cash ratio of distant markets, and wealth accumulation through deposits increases households’ demand for collateralized loans, motivating more branches to open in distant markets,

³In Online Appendix 4.5, we show that the model cannot generate hump-shaped income Gini dynamics if branch locations are randomly chosen. Thus, it is important to consider regional heterogeneity so that the model can predict a geographic distribution of branches in line with the data.

further facilitating wealth accumulation. By contrast, subsidizing branches only generates a moderate increase in the deposit-cash ratio of distant markets. However, this policy has a larger effect on promoting wealth accumulation than subsidizing households because it results in more new branch openings in distant markets. This suggests that subsidizing branches is more effective in mobilizing rural funds, highlighting the importance of promoting financial inclusion through increased access to bank branches. Furthermore, we show that the two policies have the opposite implications for income inequality. Subsidizing branches boosts the income growth of distant markets that previously had limited access to finance, resulting in a reduction in overall income inequality. However, subsidizing households leads to higher overall income inequality, as talented and wealthy households benefit more than other households from a reduced portfolio adjustment cost.

Related Literature. Our paper contributes to the macro-development literature that applies micro-founded general equilibrium models to study growth, inequality, and entrepreneurship.⁴ Our paper is closest to works focusing on the nexus between financial development and growth (e.g., Greenwood and Jovanovic, 1990; Greenwood, Sanchez and Wang, 2010, 2013; Buera and Shin, 2013; Midrigan and Xu, 2014; Moll, 2014). Motivated by the theoretical work of Greenwood and Jovanovic (1990), we emphasize the cost of accessing financial accounts, which can be naturally mapped onto the market’s distance from bank branches. A key difference between our approach and existing models is that we explicitly model local spatial markets, based on which dynamic bank expansion is evaluated, including welfare analysis and counterfactuals.⁵ By developing such a model, we shed light on the important market characteristics that determine branch locations and reproduce interesting cross-region patterns in the data.

Modeling portfolio adjustment costs dates back at least to Baumol (1952), Tobin (1956), and Miller and Orr (1966). More recently, Kaplan and Violante (2014) consider these costs in a life-cycle model to explain wealthy hand-to-mouth households with a high marginal propensity to consume. Kaplan, Moll and Violante (2018) and Alves et al. (2020) adopt this version of liquidity

⁴See, e.g., Banerjee and Newman (1993); Lloyd-Ellis and Bernhardt (2000); Quadrini (2000); Gine and Townsend (2004); Cagetti and Nardi (2006); Townsend and Ueda (2006); Jeong and Townsend (2008); Amaral and Quintin (2010); Buera, Kaboski and Shin (2011); Felkner and Townsend (2011); Kaboski and Townsend (2011); Moll (2014); Cheremukhin et al. (2015, 2017); Moll, Townsend and Zhorin (2017); Dabla-Norris et al. (2021). A complementary approach exploits randomized control trials and quasi natural experiments to study the implications of credit access (e.g., Pitt and Khandker, 1998; Karlan and Zinman, 2009; Kaboski and Townsend, 2012; Banerjee and Duflo, 2014; Augsburg et al., 2015; Banerjee et al., 2015). Recently, Bergquist et al. (2020) combine field experiments and structural models to shed light on the general equilibrium effects of policy intervention at the national level.

⁵There are extensive reduced-form studies of bank expansion (Jayaratne and Strahan, 1996; Black and Strahan, 2002; Burgess and Pande, 2005; Cetorelli and Strahan, 2006; Kerr and Nanda, 2009; Célerier and Matray, 2019; Nguyen, 2019; Fonseca and Matray, 2022), but to our knowledge, there is no formal dynamic spatial-based model to structurally evaluate the impacts of dynamic bank expansion. Aguirregabiria, Clark and Wang (2016, 2020) examine the motivation for the expansion of branch network and its implication for credit flows across locations, but they do not consider dynamic branch location choice or potential general equilibrium effects.

to study the impact of monetary policies in the context of a Heterogeneous Agent New Keynesian (HANK) model. Incorporating both liquid and illiquid assets allows the HANK model to capture realistic microeconomic consumption behavior and a sizable marginal propensity to consume out of transitory income, playing an important role in determining the policy impact. We follow [Kaplan and Violante \(2014\)](#) and adopt this friction for the savings side of our model, though we consider liquid assets as cash to fit the Thai context. Other studies emphasize heterogeneity in the effects of monetary policies ([Doepke and Schneider, 2006](#); [Auclert, 2019](#)). In New Keynesian models, the price level is determined not by the money supply but mechanically, to ensure the validity of the other variables. Similarly, in our model, the money supply (currency outstanding) is adjusted in the background to keep the real price level constant. [Wang \(2020\)](#) assumes that all financial intermediation takes place through commercial banks, as we do, but for us savers and borrowers are endogenously determined. [Corbae and D’Erasmus \(2021\)](#) develop a model of banking industry dynamics for bank capital requirements. For tractability, they distinguish large banks from a large competitive fringe. We explicitly model bank branches and their expansion in space, at a granular level.

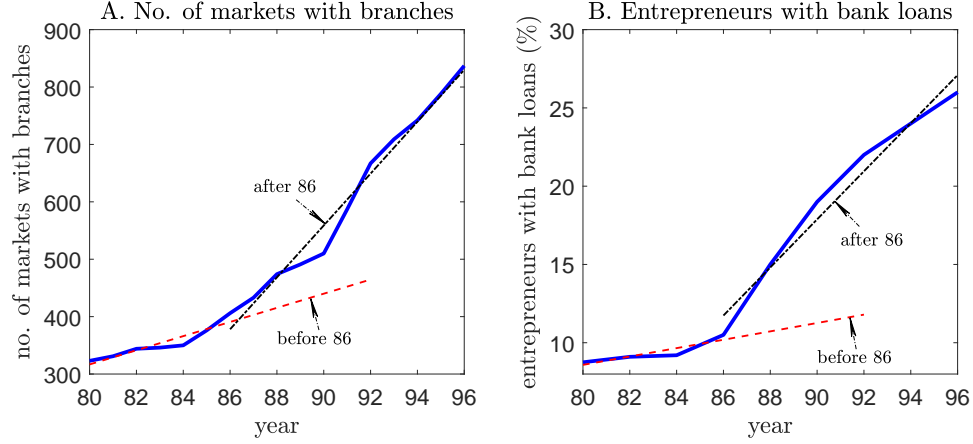
Our paper is related to the literature emphasizing the role of spatial heterogeneity in trade, growth, and development.⁶ Our paper is closest to [Desmet and Rossi-Hansberg \(2014\)](#), as we develop a dynamic model of growth with an explicit emphasis on geography and locations. However, our paper differs from theirs in several respects. First, our focus is on transitional dynamics after branching deregulation, whereas [Desmet and Rossi-Hansberg \(2014\)](#) focus on the balanced growth path of endogenous innovation. Second, our model considers a discrete number of markets and a continuum of heterogeneous households within each market, whereas [Desmet and Rossi-Hansberg \(2014\)](#) consider a continuum of markets (i.e., locations) and a representative agent in each market.⁷ Modeling heterogeneous agents in each market allows us to better connect our theory with household data, so as to capture the rich interaction between inequality, spatial growth, and the macroeconomy ([Heathcote, Storesletten and Violante, 2009](#); [Güvenen, 2011](#); [Ahn et al., 2018](#); [Kaplan and Violante, 2018](#)). Third, we propose a tractable numerical algorithm that solves the types of models that we consider, which is one of the principal contributions of our paper.⁸

The rest of the paper is organized as follows. We introduce the spatial data, define the markets, and provide empirical evidence for the market-level impacts of branch openings in

⁶See [Redding and Rossi-Hansberg \(2017\)](#) for a comprehensive review.

⁷Our modeling approach is natural given that our purpose is to evaluate bank expansion, during which a discrete number of branches are opened in each period of the data. The structure adopted by [Desmet and Rossi-Hansberg \(2014\)](#) and [Desmet, Nagy and Rossi-Hansberg \(2018\)](#) yields elegant and tractable static policy functions in a dynamic model with forward-looking agents. Their framework is tractable for analyzing questions regarding spatial concentration and inter-regional trade.

⁸See [Desmet and Rossi-Hansberg \(2014, footnote 1\)](#) for a discussion of the challenges faced by this type of spatial equilibrium models.



Note: Panel A plots the number of markets with at least one commercial bank branch, using data from the Bank of Thailand and various other financial institutions. Markets are defined and constructed in Section 2.2. Panel B plots the fraction of entrepreneurs with access to bank loans, obtained from the Thai Socio-Economic Survey. In each figure, the red dashed line is a linear curve fitting the data points between 1980 and 1986, to capture the trend before 1986; and the black dash-dotted line is a linear curve fitting the data points between 1986 and 1996, to capture the trend after 1986.

Figure 1: Bank branches and credit access in Thailand, 1980-1996.

Section 2. The model is described in Section 3 and calibrated in Section 4. In Section 5, we evaluate the model’s prediction on branch locations, shedding light on the role played by different market characteristics. In Section 6, we evaluate the aggregate and distributional impacts of bank expansion through the lens of the model. In Section 7, we apply the model to analyze policy counterfactuals. Finally, Section 8 concludes.

2 Spatial Data, Markets, and Evidence

We present empirical facts in Thailand to motivate the development of our spatial equilibrium model of dynamic bank expansion. We focus on the decade of 1986-1996, during which the Thai economy underwent swift economic growth characterized by uneven financial deepening and the rapid expansion of commercial bank branches.⁹ Thailand provides an ideal economic setting for the quantitative application of our model because of its detailed GIS data on bank branch locations and road networks, which we use in combination with household and village surveys. However, our model is not peculiar to Thailand; in future, we hope to extend the analysis to other countries.

In the late 1970s, the Thai economy reached a crossroads, as the over-regulated financial

⁹We exclude the 1997 crisis from our analysis and examine growth period before the crisis because we want to understand the endogenous links between financial deepening, growth, and inequality across regions. In Online Appendix 4.8, we show that the model-implied transitional dynamics between 1986 and 1996 would be virtually unchanged even if households fully anticipated the 1997 financial crisis.

system began to hinder the development of the economy. In 1981, the Thai Government, which was aware of the problem, invited the World Bank to examine its financial system. In response, the World Bank recommended liberalizing licensing restrictions on banks to permit universal banking and gradually abolishing interest-rate ceilings (Fry, 1986). In broad agreement with the recommendations, Thailand adopted a series of policies from the late 1980s to deregulate its financial sector, including liberalizing bank branching and alleviating the entry barriers to the banking sector. In particular, these reforms included making licensing requirements for financial institutions less restrictive, providing them with greater freedom to open new branches, and reducing excessive capitalization requirements (Gine and Townsend, 2004; Abiad, Oomes and Ueda, 2008; Townsend and Ueda, 2010). Initially, the reforms were implemented gradually, but they accelerated significantly as the real economy expanded rapidly from 1987.

Up to 1986, the Thai government imposed strict bond-holding requirements for new branch openings, equivalent to 16% of a bank’s total asset value. As a result, the commercial banks were the largest holders of government bonds in Thailand during the 1980s. However, the low returns on these bonds created significant barriers to bank branching.¹⁰ To encourage the expansion of branches, these requirements were gradually reduced to 7% between 1986 and 1992, with a further lifting of requirements in 1993 (Beng, 1994; Okuda and Mieno, 1999).

These deregulatory policies lifted the entry barriers to bank branching, leading to a significant expansion of commercial banks’ branch networks. Panel A of Figure 1 shows that the number of markets with commercial bank branches rose slowly before 1986, but more than doubled over the next decade, from 1986 to 1996. Many branches were opened in underdeveloped areas to improve financial inclusion. As a result, the fraction of entrepreneurs with access to bank loans, which was almost stagnant before 1986, increased from about 10% in 1986 to more than 26% in 1996 (see panel B of Figure 1).

In the remainder of this section, we introduce our GIS data, construct local spatial markets, and provide reduced-form evidence for the local effects of branch openings.

2.1 Spatial Data

We obtain our GIS data from the Thailand Environment Institute; the data comprise high-resolution spatial data on branch locations, political boundaries at various administrative levels, and digitized major and minor road networks, including the spatial geometry of roads, railroads, future segments, and intersections nationwide. We use the ArcGIS Network Analyst tool to construct local spatial markets and build the transportation network in each year. In total, 59,238

¹⁰For example, the International Financial Statistical Yearbooks indicate that between 1982 and 1990, the average government bond yield was 9.2% below the average commercial bank loan rate, 1.9% below the average deposit rate, and 1.3% below the average money market rate.

junctures are connected by seven types of roads. We estimate the average vehicle speed for each type of road based on real-time information and obtain the car travel time for every road segment (see Online Appendix 1.1). The road network remains largely unchanged for our study period, 1986-1996.¹¹ Commercial bank branch locations in each year are constructed using data from the Bank of Thailand.¹²

2.2 Local Spatial Markets

In Thailand, commercial bank branches are generally opened in populous regions where households engage in market activity. Thus, branch locations are informative about the locations of marketplaces. Although our study period for model evaluation is 1986-1996, our definition of markets is based on actual commercial bank branch locations in 2011, the latest year of data available to us. In total, we identify 1,428 branch locations, based on which we define the local markets that we use as actual and potential branch locations in the study period.

As an illustration, Figure 2 presents the local spatial markets based on GIS data for one province and how they map onto our model (which is developed in Section 3). In panel A, the large yellow nodes represent the branch locations in 2011. In any given year between 1986 and 1996, some of these locations may or may not have branches in the data. The black lines that divide the province into multiple regions represent the borders of local spatial markets, and the thin gray lines represent the road network. Each market contains a single branch location, and the travel time between any point on the market border and the branch locations in adjacent markets is identical. We ignore the travel time within a market for tractability, which is equivalent to assuming that households from different villages (small gray dots) within a market are all located at the branch location enclosed in the market. Panel B presents our model economy (see Section 3) which consists of the local spatial markets corresponding to the branch locations in panel A. These markets are connected via road links, forming a network.

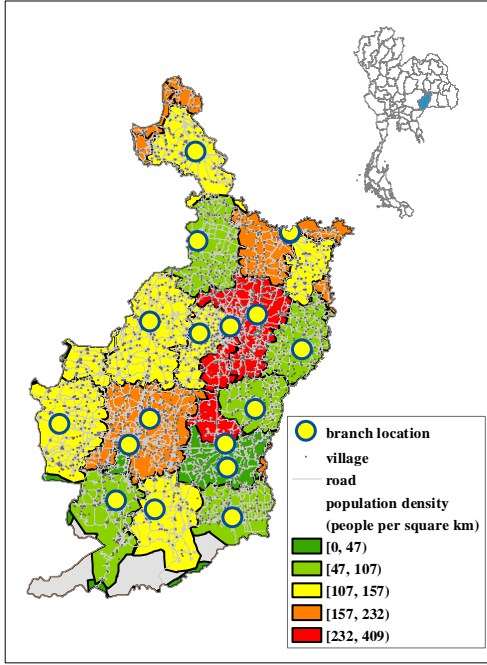
2.3 Empirical Evidence

In this section, we provide direct evidence of the impact of branch expansion on several market-level variables that capture local economic activities or characteristics. These variables include

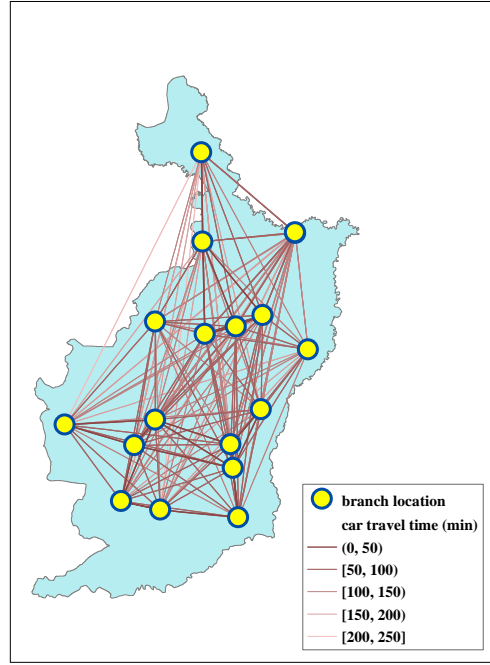
¹¹Felkner and Townsend (2011) compare the Thai government road data with more recent maps obtained from American Digital Cartography as well as with current Thai road maps and Google Maps data. Their comparisons indicate that no new primary roads (highways and high-quality paved roads) were constructed after 1986. We provide photographs of road networks in different years and more detailed discussions in Online Appendix 1.1.

¹²Our paper focuses on the expansion of branches by commercial banks, which are the central players in the Thai financial system. Commercial banks account for 80.9% of deposits and 73.1% of total financial system assets during our study period. We do not consider the branches of the Bank for Agriculture and Agricultural Cooperatives (BAAC), a state-owned enterprise.

A. Local spatial markets based on GIS data



B. Mapping onto the model



Note: Panel A plots the local spatial markets based on GIS data for Buriram province in Thailand. The yellow nodes represent commercial bank branch locations, and the small gray dots represent villages. The black lines represent the borders of each market, and the thin gray lines represent the road network. The different colors of the markets indicate their population densities, equal to the markets' population divided by their area, computed from the GIS data. Panel B plots the province in our model economy (see Section 3). The yellow nodes correspond to the local spatial markets that enclose the branch locations in panel A. These markets are connected by links, and the distance between each pair of markets is measured by car travel time along the actual road network.

Figure 2: An illustration of local spatial markets based on GIS data and the model.

employment, income per capita, the fraction of households with commercial bank loans, and the fraction of entrepreneurs, constructed by aggregating the village-level data from the Thai Community Development Department (CDD), a complete village census of over 60,000 villages, which has been conducted since 1986 (see Online Appendix 1.2 for details).

2.3.1 Research Design

The endogenous nature of branch expansion poses identification challenges in our analysis. In general, banks are likely to open branches in markets with favorable growth prospects. Such markets may be characterized by low credit access and high business dynamism, implying high potential growth opportunities in the future. Thus, simply comparing markets where branches are open and those without branches would produce a biased estimate of the impact of branch openings.

There is no perfect strategy for tackling the endogeneity issue due to the absence of exogenous

variations in the locations of branches in our setting. One commonly used strategy is the DID method, the validity of which depends on whether the treatment and control groups are sufficiently comparable. There are two main concerns in relation to using the DID method in our context. First, the treatment group could differ from the control group in certain observable and unobservable characteristics, which may determine the evolution of outcome variables. Second, the standard DID method simply controls for time and market fixed effects without properly specifying the control group. For example, for a market treated in year t , its control group includes markets that do not receive the treatment in year t , which could be markets that were treated before year t and markets that will be treated after year t . As emphasized by Kaplan and Violante (2014), in the former case, the estimated effect can be influenced by the lagged effect of past treatment in control markets. In the latter case, it can be influenced if there is anticipated future treatment in control markets.

To address these concerns, we apply the DID method to matched treatment and control markets (e.g., Jager and Heining, 2019; Smith et al., 2019; Fonseca and Matray, 2022). Specifically, we base our empirical estimation on the 1986-1996 period, which commences after the relaxation of the branching requirement in 1986. The treatment markets are those in which a branch is opened. For each treatment market, we find a matched control from a “donor pool,” which only includes markets that do not have any branches by 1996.¹³ We exclude all markets that already have branches before our study period for two reasons. First, this is consistent with the model developed in Section 3, which focuses on evaluating the new branches opened between 1987 and 1996. Second, the restricted donor pool ensures that the estimates are not confounded by the lagged effect of past branch openings in control markets. We improve the comparability between the treatment and control groups by ensuring that each treatment market and its matched control market have similar propensity scores before the treatment. Guided by our model, we estimate the propensity score based on four covariates that are likely to be correlated with the choice of branch locations and our outcome variables of interest.¹⁴ After matching, we obtain a panel

¹³In Online Appendix 3.9, we evaluate how the anticipated and lagged effects of branch openings in control markets affect our DID estimates using the simulated data of our structural model developed in Section 3. We find that in the model, the anticipated effect of branch openings in control markets does not greatly change the estimated effects of branch openings. Thus, to have a sufficiently large number of markets in our donor pool for matching purposes, we do not further restrict the size of the donor pool by requiring markets to have no branch openings beyond 1996.

¹⁴The four covariates are population, distance from the nearest bank branch, the type of cooking fuel (gas or coal), and the fraction of households with pickup trucks. We choose these variables not only because conceptually they may influence the choice of branch locations, but also because they accord with our model’s findings. As discussed in Section 5.2, our model implies that three market characteristics (i.e., size $\Pi_{i,t}$, productivity Z_i , and distance from the nearest branch $d_{i,t}$) largely explain the locations of branches opened during the 1987-1996 period. The first two variables capture $\Pi_{i,t}$ and $d_{i,t}$ in our model, and the other two variables (the type of cooking fuel and the fraction of households with pickup trucks) are indicative of market productivity. To address concerns with potential matching errors, we conduct robustness checks using coarsened exact matching and nearest neighbor matching to form pairs of treatment and control markets (see Online Appendix 2.2).

consisting of treatment and matched control markets, balanced in terms of the covariates (see Table OA.2 in Online Appendix 2.1).

Thus, our empirical strategy essentially exploits variations in branch locations and the timing of their establishment in a DID framework with staggered treatment, similar to that used by Greenstone and Hanna (2014) and Bailey and Goodman-Bacon (2015), except for additionally matching treatment and control markets by covariates. Following Jager and Heining (2019), we run the following regression:

$$y_{it} = \sum_{\tau=-3}^2 \alpha_{\tau} \times D_{it}^{\tau} \times Treated_i + \sum_{\tau=-3}^2 \beta_{\tau} D_{it}^{\tau} + \mu_i + \epsilon_{it}, \quad (2.1)$$

where $Treated_i$ and D_{it}^{τ} are two dummy variables for market i . We include leads and lags around the event time. It is straightforward to explain specification (2.1) by focusing on treatment market i and its matched control market \bar{i} . The dummy variable $Treated_i$, which shows up only in the first term of equation (2.1), captures whether the market is treated (i.e., whether a branch is opened between 1987 and 1996), so we have $Treated_i = 1$ and $Treated_{\bar{i}} = 0$. The dummy variable D_{it}^{τ} , which appears in the first and second terms of equation (2.1), is identical for market i and its matched control market \bar{i} . Specifically, both D_{it} and $D_{\bar{i}t}$ are determined according to the difference between calendar year t and the treatment year (i.e., the branch-opening year) of treatment market i . We have $D_{it}^{\tau} = D_{\bar{i}t}^{\tau} = 1$ if a bank branch is opened in year $t - 2\tau - 1$ or $t - 2\tau - 2$ in treatment market i .¹⁵ For example, $\tau = 0$ means that the branch in treatment market i is opened in year $t - 1$ or $t - 2$, indicating that in calendar year t , the branch has been open for 1-2 years. Thus, the coefficient α_0 , which captures the average difference in the outcome variable between the treatment and control markets across all matched pairs, estimates the average treatment effect in the first 2 years after a branch is opened. The variable μ_i (and $\mu_{\bar{i}}$) captures market fixed effects.¹⁶

2.3.2 Empirical Results

Table 1 presents the results. Columns (1)-(2) show that local employment and income per capita increase by about 18.6% and 17.4%, respectively, in the 2 years following a branch opening.¹⁷

¹⁵The variable τ is multiplied by 2 because the CDD data are biennial. We do not have issues when estimating the lead and lag effects for the years at the beginning or end of our study period because our branch location data span a longer period, 1980-2011. Following Bailey and Goodman-Bacon (2015), all observations more than 4 years before and after the treatment are captured by dummies D_{it}^{-3} and D_{it}^2 , respectively.

¹⁶Equation (2.1) does not include year fixed effects because the calendar year is balanced between the treatment and control groups following our matching procedure. Introducing year fixed effects does not change the point estimates of the treatment effect.

¹⁷In our empirical setting, the stable unit treatment value assumption (SUTVA) is likely not satisfied due to the spillover effects of branch openings on nearby regions, as indicated by the model developed in Section 3. Thus, rather than interpreting these estimates as capturing the treatment effect on the treated, it is more appropriate to

Similar to the findings of [Barboni, Field and Pande \(2022\)](#) and [Fonseca and Matray \(2022\)](#), we estimate large effects of branch openings on employment and income.¹⁸ These estimates are reasonable for Thailand during our study period because, before 1986, most markets had no branches and were virtually in a state of financial autarky. Due to the underdeveloped financial system, few household members were employed as wage earners, and most were self-employed farmers earning a subsistence level of income (e.g., [Gine and Townsend, 2004](#); [Townsend and Ueda, 2006](#); [Jeong and Townsend, 2008](#)). Although we do not have high-quality data for the fraction of farmers in each market, at the aggregate level, 46% of households in Thailand were farmers in the agricultural sector in 1986. Thus, the large increases in employment and income per capita after branch openings estimated here are related to the economy transitioning away from agriculture to manufacturing. Moreover, the markets on which we focus are small areas, with radiuses of 3 - 5 *km*, which is another factor explaining why the first branch openings have such economically significant local effects.

Columns (3)-(4) of Table 1 provide evidence suggesting that the increases in local employment and income per capita can be attributed to the increases in local credit access and entrepreneurial activities. Column (3) shows that more households start their own businesses after a branch opening than before, as indicated by the 2.3% increase in the fraction of entrepreneurs in the first 2 years. This is a large effect in terms of percentage change, as the average fraction of entrepreneurs in the population in 1986 was about 15.4%. Column (4) shows that in the first 2 years after a branch opening, the credit access ratio (i.e., the fraction of households with access to commercial bank loans) increases by about 3.4%. The magnitude of this effect is larger than the effect of branch openings on the fraction of entrepreneurs, suggesting that some entrepreneurs who lack credit access before a branch opening, choose to borrow from the local bank to finance their businesses. Again, the effect on the credit access ratio is large, given that the average credit access ratio was about 1.6% in 1986, and 363 markets had virtually no credit access ($< 0.01\%$). While we do not have data for loan amounts, in principle, financial development can improve credit access through both the extensive margin (the fraction of households with credit access) and the intensive margin (loan amounts for those who already have access), e.g., [Greenwood and Jovanovic \(1990\)](#), [Buera and Shin \(2011\)](#), [Greenwood, Sanchez and Wang \(2013\)](#), and [Dabla-Norris et al. \(2021\)](#). For example, [Fonseca and Matray \(2022\)](#) exploit the expansion of government-owned banks in Brazil and estimate that opening a branch increases loans in treated cities by 1.7%-3.4% of local GDP. [Nguyen \(2019\)](#) estimates large negative local effects of branch

interpret them as capturing the treatment effect on the treated relative to the control.

¹⁸Using an experiment that randomizes bank branch placement over 870 villages in rural India, [Barboni, Field and Pande \(2022\)](#) estimate that household income and business sales increase by 14% and 21%, respectively, in treated villages. [Fonseca and Matray \(2022\)](#) estimate that the expansion of government-owned banks in Brazil increases firm employment in treated cities by 10% in 2 years, and the effect more than doubles in treated cities that were distant from existing banks before the expansion.

Table 1: Impact of opening bank branches on local economic variables.

	(1)	(2)	(3)	(4)
	ln(Employment)	ln(Income per capita)	Fraction of entrepreneurs	Fraction of HH with bank loans
$\hat{\alpha}_{-3}$	-0.043 (0.103)	-0.071 (0.104)	-0.012 (0.016)	-0.006 (0.012)
$\hat{\alpha}_{-2}$	-0.013 (0.097)	-0.009 (0.088)	-0.001 (0.015)	-0.007 (0.011)
$\hat{\alpha}_0$	0.186 (0.092)	0.174 (0.089)	0.023 (0.013)	0.034 (0.009)
$\hat{\alpha}_1$	0.305 (0.104)	0.294 (0.094)	0.035 (0.016)	0.039 (0.011)
$\hat{\alpha}_2$	0.341 (0.115)	0.324 (0.102)	0.040 (0.015)	0.038 (0.012)
No. of branch openings	423	400	393	434
No. of observations	5,076	4,000	4,716	5,208

Note: This table presents the estimates of the impact of opening bank branches on local economic variables using the DID method (equation (2.1)) on matched pairs of treatment and control markets. The matching procedure is based on market-level propensity scores. The dependent variables in columns (1)-(4) are market-level log employment, log income per capita, the fraction of entrepreneurs, and the fraction of households (HH in the table) with commercial bank loans, respectively. All coefficients are normalized relative to $\tau = -1$. Following [Bertrand, Duflo and Mullainathan \(2004\)](#), standard errors reported in parentheses are clustered at the market level to address potential concerns of serial correlation of outcomes across periods.

closings in the U.S. Using tract-level data (where the median tract is about 1.5 square miles), [Nguyen \(2019\)](#) estimates that over the 6 years following a branch closing, the number of new small business loan originations declines by 62.3 cumulatively from a baseline mean of 103.4; and the dollar volume of new lending declines by \$5.2 million cumulatively from a baseline mean of \$4.7 million per year.

Figure 5 visualizes the estimated effects shown in Table 1. The leading terms of the estimated treatment effects are close to 0 and statistically insignificant, suggesting that the parallel trend assumption is satisfied in the years before the treatment. Furthermore, to show the robustness of our estimates, we present the results of DID estimation with alternative matching methods and the synthetic control method (e.g., [Abadie and Gardeazabal, 2003](#); [Abadie, Diamond and Hainmueller, 2010](#)) in Online Appendices 2.1 and 2.2. We find that different strategies produce results of similar economic magnitudes. Although none of them can perfectly address the identification issue, the similarity in the results bolsters our confidence that our main identification strategy based on DID with propensity score matching estimates the effect of opening bank branches on these local economic variables.

3 Model

To rationalize the micro evidence, we develop a spatial equilibrium model by incorporating local spatial markets and bank expansion to a growth model featuring financial frictions (e.g., Greenwood, Sanchez and Wang, 2010; Buera and Shin, 2013; Midrigan and Xu, 2014).

3.1 Basic Environment

Time is discrete and indexed by $t \geq 0$. The economy consists of N markets, indexed by $i \in \mathcal{C} = \{1, \dots, N\}$, representing different geographic regions. Markets are connected by roads. Denote by τ_{ij} the distance between the central nodes of markets i and j . The road network is complete, meaning that τ_{ij} exists for all $i, j \in \mathcal{C}$, with $\tau_{ij} \equiv 0$ for $i = j$. Although the road network is fixed exogenously, the financial intermediation network evolves endogenously over time because of new branch openings.

Markets differ from each other in three dimensions. First, they differ in their size $\Pi_{i,t}$, which captures the measure of households in market i at time t . The variable $\Pi_{i,t}$ has a time-subscript t because households are allowed to migrate across markets. We describe household heterogeneity and decisions in Section 3.2.

Second, markets differ in their access to finance, captured by the distance from the nearest bank branch $d_{i,t}$ for market i at time t . Some markets have bank branches while others do not. Households in markets with bank branches can take out loans or make deposits locally, whereas those in markets without branches must travel to nearby markets at a cost that depends on $d_{i,t}$. The variable $d_{i,t}$ has a time subscript t because of branch expansion over time.

Third, markets differ in their productivity Z_i (e.g., Acemoglu and Dell, 2010; Kleinman, Liu and Redding, 2021), which determines the amount of output produced by local entrepreneurs. We introduce market-specific productivity Z_i to capture the fundamental differences across markets that are not entirely explained by $\Pi_{i,t}$ or $d_{i,t}$. For example, some markets could have higher income per capita than others because they are located in more favorable geographic regions, which may in turn attract bank branches. For simplicity, we assume that Z_i is constant over time.

Our model focuses on the dynamic expansion of bank branches. To maintain tractability, we take the number of new branch openings n_t in each period t as exogenously given, and focus on modeling the endogenous choice of these branch locations, as detailed in Section 3.3. The three market characteristics play important roles in aligning the model-implied branch locations with those in the data (see Section 5.2).

For realism, we assume that a branch has capacity h to serve households. Households from other markets can obtain financial services from market i 's branch only when market i 's size is

smaller than the branch's capacity, i.e., $\Pi_{i,t} < h$.¹⁹ We use the binary indicator $B_{i,t}$ to denote whether market i has a branch at time t ($B_{i,t} = 1$) or not ($B_{i,t} = 0$). Denote by Ψ_t the set of markets with bank branches at time t , i.e., $\Psi_t = \{i : B_{i,t} = 1, i \in \mathcal{C}\}$. The set Ψ_t evolves endogenously due to new branch openings over time. Thus, for $i \in \Psi_t$, we have $d_{i,t} = 0$, and for $i \notin \Psi_t$, we have

$$d_{i,t} = \min \{\tau_{ij} : j \in \Psi_t, \Pi_{j,t} < h\}. \quad (3.1)$$

In our model, the distance from the nearest bank branch $d_{i,t}$ plays an important role in determining the degree of financial frictions in market i .

3.2 Households

Heterogeneity and Demographics. There is a continuum of households of measure $\Pi_{i,t}$ in market i at time t . Households live indefinitely and are heterogeneous in four dimensions: talent z_t , cash m_t , deposits a_t , and market i in which they live. For brevity, in the rest of this section, we omit the index for an individual household.

Talent z_t follows an exogenous stochastic process. With probability γ , households retain their talent from the previous period, i.e., $z_t = z_{t-1}$, and with probability $1 - \gamma$, households draw new talent z_t from a time-invariant Pareto distribution $\Gamma(z)$ governed by the tail parameter ρ . Shocks to talent can be interpreted as changes in the conditions that affect the profitability of individual skills (e.g., Buera, Kaboski and Shin, 2011).

The wealth of households consists of cash m_t and deposits a_t as a claim on the bonds acquired by banks in lending to firms. Both assets are denominated in consumption units. Households can purchase consumption goods c_t and capital k_t using cash m_t , but they cannot use deposits a_t to do so.²⁰ The tradeoff between the two saving instruments is that cash earns no return, whereas deposits earn the interest rate $r_t > 0$ in equilibrium. Transforming cash into deposits or vice versa requires households to pay the market-specific portfolio adjustment cost of going to the bank.²¹ This tradeoff between cash m_t and deposits a_t is highly reminiscent of the main insight

¹⁹For tractability, we exclude consideration of rationing caused by capacity h by making the following assumptions. If market i has a branch, households living in market i can always obtain financial services locally with probability 1 regardless of market size $\Pi_{i,t}$. When $\Pi_{i,t} < h$, households traveling to market i from other markets can always obtain financial services with probability 1.

²⁰Because our goal is to evaluate bank expansion, our model focuses on spatial heterogeneity in accessing financial accounts. For tractability, we do not introduce heterogeneous prices of goods or capital across local spatial markets. Desmet and Rossi-Hansberg (2014) and Monte, Redding and Rossi-Hansberg (2018) develop models that emphasize spatial links in goods markets. Interestingly, even in the same geographic area, the prices of identical goods can differ significantly across stores and households (Kaplan and Menzio, 2015; Kaplan et al., 2019), and such patterns can be explained by search frictions in product markets (Menzio and Trachter, 2015; Kaplan and Menzio, 2016; Menzio and Trachter, 2018).

²¹As in Kaplan and Violante (2014), the quantitative implications of our model do not depend on whether the portfolio adjustment cost is specified in terms of consumption units or disutility.

of optimal cash management models (Baumol, 1952; Tobin, 1956; Miller and Orr, 1966; Alvarez and Lippi, 2009). A lower portfolio adjustment cost motivates households to put more of their wealth into deposits.

Denote by $\zeta_{i,t}$ the portfolio adjustment cost in market i at time t . We specify that $\zeta_{i,t} \equiv \zeta(d_{i,t})$, with $\zeta(d_{i,t})$ increasing with $d_{i,t}$. The cost $\zeta_{i,t}$ captures various fees associated with financial accounts, bookkeeping and exchange costs (e.g., Townsend, 1983), and transportation costs to bank branches, which include both monetary and time costs and increase with $d_{i,t}$. During our study period (1986-1996), the transportation costs to bank branches in Thailand are important due to the lack of online banking and the government’s restrictions on the operation of ATMs. Most ATMs were located within bank branches and open only during the day (Okuda and Mieno, 1999). Moreover, trips to bank branches are particularly costly for low-income households because of the relative scarcity of bank branches in their local neighborhoods (Caskey, 1994).²² The empirical findings in the literature suggest that geographic proximity to bank branches matters. For example, Célerier and Matray (2019) exploit the U.S. interstate branching deregulation over the 1994-2005 period and find that the presence of local bank branches significantly increases the use of bank accounts by low-income households. Stein and Yannelis (2020) use data from Freedman’s Savings Bank and find that individuals in a county with a branch are 13-17 percentage points more likely to hold an account than those living in a county without a branch. Fonseca and Matray (2022) exploit the expansion of government-owned banks in Brazil and estimate that opening a branch increases deposits in treated cities by 1.6%-2.4% of local GDP. Modeling distance-dependent portfolio adjustment costs enables us to incorporate the effect of bank expansion on aggregate savings, which constitutes the deposit channel of bank expansion.²³ In Online Appendix 3.3.3, we show that the average deposit-cash ratio (a_t/m_t) in market i decreases with $d_{i,t}$ in our model, and in Online Appendix 2.3, we provide some suggestive evidence from the Townsend Thai data.

Our modeling approach of the two assets m_t and a_t is similar in spirit to that of Kaplan and Violante (2014).²⁴ Bonds/deposits are liquid in the U.S. but not in developing countries. As in Kaplan and Violante (2014), households choose consumption after making portfolio adjustments

²²Transportation costs due to distance could be further amplified by uncertainty about service times. Households may feel reluctant to travel long distances to make deposits or withdrawals if with certain probabilities, they need to wait in a queue for a long period to be served by bank tellers. However, with short distances, households can easily check the queue and leave if it is too long (De Vany, 1976).

²³Studies find that highly developed financial markets promote growth by raising domestic savings rates (e.g., King and Levine, 1994; Fry, 1995; Bandiera et al., 2000).

²⁴Such two-asset models have been commonly adopted in recent macroeconomic models (e.g., Heathcote and Perri, 2018; Kaplan, Moll and Violante, 2018; Bayer et al., 2019; Auclert, Rognlie and Straub, 2020; Kaplan, Mitman and Violante, 2020), because they can be calibrated to generate realistic microeconomic consumption behavior and heterogeneous households’ marginal propensity to consume, both of which are closely related to households’ access to liquidity (Mian, Rao and Sufi, 2013; Kaplan, Violante and Weidner, 2014; Fuster, Kaplan and Zafar, 2021). Early generations of two-asset models assume that portfolio adjustments can be made at given frequencies (e.g., Alvarez, Atkeson and Edmond, 2009; Alvarez and Lippi, 2009).

within each period. This timing assumption implies that our model does not feature a cash-in-advance constraint.

Preferences. Households derive utility from consumption c_t and have the following preferences

$$\mathbb{E}_t \left[\sum_{t'=t}^{\infty} \beta^{t'-t} \frac{c_{t'}^{1-\sigma}}{1-\sigma} \right], \quad (3.2)$$

where β is the discount factor and σ captures risk aversion.

Occupation Choice and Technology. In each period t , households can choose from three occupations: worker, farmer, or entrepreneur. Workers supply one unit of labor inelastically and earn the endogenous market-specific wage $w_{i,t}$. Farmers earn a subsistence income fZ_i , which is exogenous and proportional to the market's productivity Z_i . Entrepreneurs operate a technology that uses capital k_t and labor l_t to produce output $q_i(k_t, l_t, z_t)$,

$$q_i(k_t, l_t, z_t) = Z_i z_t (k_t^\alpha l_t^{1-\alpha})^{1-\nu}, \quad (3.3)$$

where output increases with market productivity Z_i and household talent z_t . The parameter ν determines the span of control (e.g., Lucas, 1978; Guner, Ventura and Yi, 2008; Buera and Shin, 2011, 2013), and $1 - \nu$ represents the share of output accruing to variable factors. A fraction α of this output goes to capital and $1 - \alpha$ goes to labor. Capital k_t depreciates at rate δ . For tractability, we assume that in each period, before production, households can buy capital k_t at a unit price, using cash m_t , from a centralized capital shop; after production, households sell their remaining capital $(1 - \delta)k_t$ to the capital shop at the same price. This is essentially the same as allowing households to freely transform cash m_t into capital k_t or vice versa at a unit conversion rate. Thus, k_t is not a state variable given a_t and m_t .²⁵ Similar modeling approaches to frictionless capital rental markets are adopted in the macro-finance literature (e.g., Jorgenson, 1963; Buera and Shin, 2013; Moll, 2014; Dou et al., 2021, 2022).

In each market i and period t , the equilibrium wage $w_{i,t}$ is determined to clear the local labor market. Heterogeneous productivities Z_i and degrees of financial frictions $d_{i,t}$ endogenously drive the differences in wages, entrepreneurial activities, and outputs across markets.

²⁵The assumption of frictionless capital adjustment affects the model's quantitative implications for the deposit channel (i.e., the reduction in $\zeta_{i,t}$) of bank expansion as well as the calibration of $\zeta_{i,t}$. In Section 6.1, we show that the quantitative effect of the deposit channel is smaller than that of the credit channel (i.e., the reduction in $\psi_{i,t}$) of bank expansion. The effect of the deposit channel would be reduced further if we allow entrepreneurs to accumulate capital (as a state variable), so they do not need to withdraw cash to buy capital.

Frictions in Credit Markets. Following Buera and Shin (2011), we focus on within-period credit for production purposes. We do not allow households to borrow for consumption smoothing by imposing $m_t, a_t \geq 0$. The interest rate r_t is determined endogenously by the economy-wide capital-market clearing condition. The lending rate r_t^l is higher than the interest rate r_t by a margin χ , which determines the profits of financial intermediation that accrue to banks.

There is limited participation in the credit market. To obtain a loan, entrepreneurs need to pay an upfront market-specific credit entry cost using cash m_t , as in Greenwood and Jovanovic (1990). Denote by $\psi_{i,t}$ the credit entry cost in market i at time t . A lower $\psi_{i,t}$ motivates more entrepreneurs to borrow, increasing credit access.

Motivated by the empirical evidence that road distance and branch density affect credit access (e.g., Nguyen, 2019; Agarwal, Mukherjee and Naaraayanan, 2022; Fonseca and Matray, 2022), we specify that $\psi_{i,t} \equiv \psi(d_{i,t})$, where $\psi(\cdot)$ is a strictly increasing function, meaning that it is more costly to borrow if market i is further away from bank branches. The distance-dependent credit entry costs $\psi(\cdot)$ can be due to both transportation and information costs. During our 1986-1996 study period, financial technology in Thailand was in its infancy, and the provision of bank loans occurred through on-site visits by loan officers. Because evaluating loan applications and monitoring borrowers usually requires multiple site visits, it was costly for banks to lend to distant borrowers, which means that they were less willing to extend loans to distant borrowers than to nearby borrowers. In addition to transportation costs, information costs faced by banks increase with distance (e.g., Elliehausen and Wolken, 1990; Petersen and Rajan, 2002; Nguyen, 2019; Fonseca and Matray, 2022). Unlike deposit markets, providing credit to households or to entrepreneurs running small businesses involves substantial credit risks due to information asymmetry. The “hard” information provided by audited financial statements is available for large corporations, but for households and small businesses, banks must rely on “soft” information, which tends to be derived from their previous dealings or knowledge of the local community and economic conditions. Consequently, banks prefer to lend to nearby prospective borrowers about whom they have superior information and whose loan performance they can monitor more easily compared with distant borrowers. In the U.S., Nguyen (2019) exploits the bank branch closures caused by mergers during the 2000s and finds that distance from branches matters for credit provision because shorter distances reduce the costs of transmitting information and facilitate the forging of long-term relationships.

The amount of capital used in production is subject to a borrowing constraint (as in Buera

and Shin, 2011, 2013; Moll, 2014; Boar, Gorea and Midrigan, 2022):²⁶

$$\xi k_t \leq m_t + a_t - \psi_{i,t}. \quad (3.4)$$

The parameter $\xi \in [0, 1]$ determines the tightness of borrowing constraints, with $\xi = 1$ representing autarky, where capital must be self-financed by entrepreneurs. Note that the portfolio adjustment cost $\zeta_{i,t}$ is not subtracted from equation (3.4) because it is incurred after production, when households make portfolio adjustments at the end of the period (see Figure 3).

Migration. One of our main goals is to develop a macro model that emphasizes spatial heterogeneity. Thus, it is natural and important to allow inter-market migration. Although our focus is on bank expansion, our calibration matches the migration flows in the data (see Section 4). The role of migration is discussed and separately quantified in Online Appendix 4.1.2.

We model household migration following the quantitative migration literature (e.g., Kennan and Walker, 2011; Caliendo, Dvorkin and Parro, 2019; Lagakos, Mobarak and Waugh, 2020). Households can choose to migrate to other markets at the end of each period t , subject to both fixed migration costs and idiosyncratic taste shocks.²⁷ Specifically, households need to pay a fixed pecuniary migration cost κ using cash m_t if they choose to migrate from their current market i to a different market $j \neq i$.²⁸ We introduce additive, nonpecuniary idiosyncratic taste shocks to capture migration decisions made for idiosyncratic reasons. In the data, there are households

²⁶A micro foundation is provided in Jermann and Quadrini (2012). Consider an entrepreneur who approaches the bank for a loan x_t . After obtaining the loan x_t , the entrepreneur buys capital $k_t = m_t + x_t - \psi_{i,t}$ using her own cash m_t and loan x_t net of the cost $\psi_{i,t}$. Both capital k_t and deposits a_t are then used as collateral to secure the loan x_t . The entrepreneur is free to default and walk away with her income and wealth at any time, but if she does, the bank will seize collateral $k_t + a_t$. We assume that the liquidation value of capital is uncertain at the time of contracting. The bank recovers the full value k_t with probability $1 - \xi$, but recovers nothing with probability ξ . Thus to avoid default, the amount of the loan x_t that the bank is willing to lend is restricted to $x_t \leq (1 - \xi)k_t + a_t$. Substituting $x_t = k_t - m_t + \psi_{i,t}$ into the loan constraint, we derive the entrepreneur's borrowing constraint (3.4).

²⁷We introduce these costs to match the migration flows in the data, following standard practice in the literature. For example, to capture the rich patterns of rural-urban migration of households with different productivity and asset levels, Lagakos, Mobarak and Waugh (2020) assume that migration is subject to a pecuniary cost, a utility cost, and idiosyncratic taste shocks. Kaplan and Schulhofer-Wohl (2017) and Lagakos et al. (2020) model migration costs as the loss of a fixed fraction of income. Both Bryan and Morten (2019) and Morten (2019) model migration costs as utility costs. Monte, Redding and Rossi-Hansberg (2018) and Tombe and Zhu (2019) also model migration costs as utility costs and show that the results remain robust if the migration cost is modeled as a decrease in labor productivity. Our results are robust if we assume instead that the fixed migration cost is nonpecuniary. Our specification is similar to that of Ehrlich and Townsend (2021), who introduce both pecuniary fixed migration costs and idiosyncratic taste shocks in the context of Thailand. Moreover, Ehrlich and Townsend (2021) assume that migration decisions are made at the end of the period for tractability.

²⁸Kennan and Walker (2011) allow the fixed cost κ to depend on migration distance, with the coefficient being identified by detailed location-to-location migration flow data. Without such data in Thailand, we assume a constant κ for simplicity. In Figure OA.28 in Online Appendix 4.1.3, we perform robustness checks and show that allowing κ to linearly increase with migration distance as in Kennan and Walker (2011) has little effect on the quantitative implications of the model.

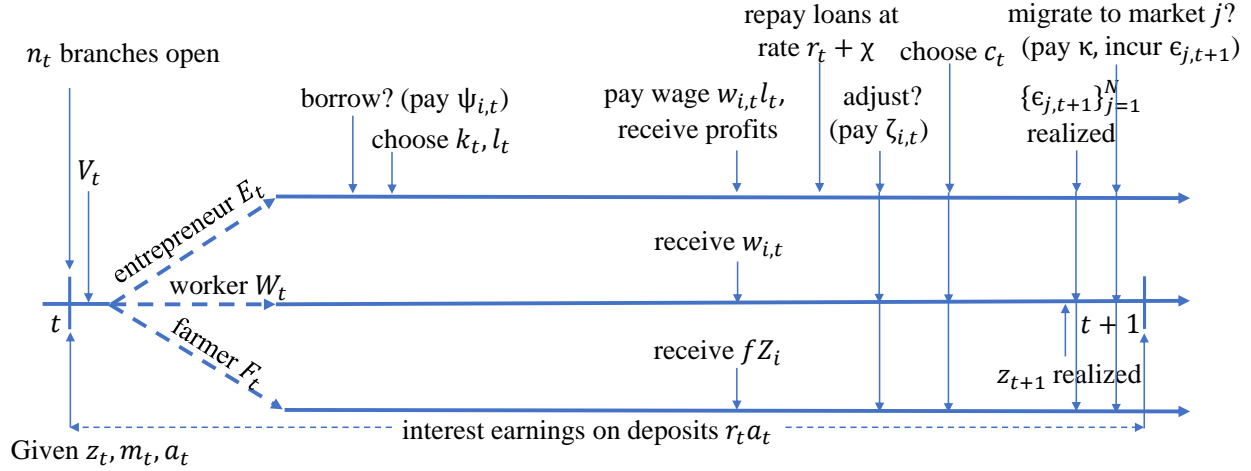


Figure 3: Timing of events.

migrating to markets with branches and households migrating to markets that are distant from branches. Introducing idiosyncratic taste shocks allows us to capture the latter group of migrants and match this empirical pattern. Following the literature (e.g., Kennan and Walker, 2011; Lagakos, Mobarak and Waugh, 2020), each household draws idiosyncratic taste shocks for each market j and period t , $\{\epsilon_{j,t}\}_{j=1}^N$, independently from a Type-I extreme value distribution with a mean of 0 and scale parameter η .

Household Problem. The timing of decisions is presented in Figure 3. At the beginning of period t , n_t new branches are opened at the places chosen by the central authority (see Section 3.3). Households make occupation choices, and those choosing to be entrepreneurs need to decide whether to borrow and make production decisions. At the end of the period, households receive subsistence incomes, wages, or production profits depending on their occupations, and repay loans (if any). Next, households decide whether to adjust their portfolio and then choose their consumption. Finally, migration taste shocks $\{\epsilon_{j,t+1}\}_{j=1}^N$ are realized, after which households decide which market to stay in for period $t+1$. For further clarity, we present households' cash flow statements in Online Appendix 3.5.

We formulate the household problem recursively. Let $\{s_t, i\}$ represent the state variables of households living in market i at time t , where $s_t \equiv \{z_t, m_t, a_t\}$. Denote by $V_t(s_t, i)$ the value function of households of type s_t living in market i at the beginning of period t . The value function has a time subscript t because we focus on transitional dynamics. Households fully anticipate changes in costs $\psi_{j,t}$ and $\zeta_{j,t}$ due to future branch openings for all $j = 1, 2, \dots, N$. Let $F_t(s_t, i)$, $W_t(s_t, i)$, and $E_t(s_t, i)$ denote the value of households in market i at time t , when they decide to be farmers, workers, or entrepreneurs, respectively. The occupation choice is made to

maximize utility,

$$V_t(s_t, i) = \max \{F_t(s_t, i), W_t(s_t, i), E_t(s_t, i)\}. \quad (3.5)$$

We describe each of these value functions in turn. The value function of farmers is $F_t(s_t, i) = \max\{F_t^0(s_t, i), F_t^1(s_t, i)\}$, where $F_t^0(s_t, i)$ and $F_t^1(s_t, i)$ are the values conditional on not adjusting and adjusting the portfolio, respectively.

Specifically, when farmers do not adjust their portfolios, the budget constraints are characterized by two equations determining the evolution of cash m_t and deposits a_t , respectively. The value $F_t^0(s_t, i)$ is given by

$$F_t^0(s_t, i) = \max_{c_t, m_{t+1}} \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_t \left[\max_{j \in \{1, \dots, N\}} \{V_{t+1}(s_{t+1}, j) + \epsilon_{j,t+1}\} \right] \right\}, \quad (3.6)$$

$$\text{s.t. } m_{t+1} + c_t = m_t + fZ_i - \kappa \mathbb{1}_{\{j \neq i\}}, \quad (3.7)$$

$$a_{t+1} = (1 + r_t)a_t, \quad \text{with } c_t, m_{t+1} \geq 0,$$

where the max operator, $\max_{j \in \{1, \dots, N\}}$, in the objective function captures households' optimal migration decisions. Households choose to migrate to market j that offers the highest continuation value $V_{t+1}(s_{t+1}, j) + \epsilon_{j,t+1}$, considering that migration is subject to the fixed pecuniary cost κ (which affects the evolution of m_{t+1} through equation (3.7) when $j \neq i$ ²⁹) and the idiosyncratic taste shock $\epsilon_{j,t+1}$, which additively affects the utility obtained in market j . The max operator is within the expectation operator $\mathbb{E}_t[\cdot]$ because migration decisions are made after the realization of idiosyncratic taste shocks $\{\epsilon_{j,t+1}\}_{j=1}^N$ (see Figure 3). Thus, the expectation operator $\mathbb{E}_t[\cdot]$ incorporates both talent z_{t+1} and taste shocks $\{\epsilon_{j,t+1}\}_{j=1}^N$. Cash m_t and deposits a_t earn returns of 0 and r_t , respectively. The variable fZ_i captures the subsistence income that farmers earn in market i at time t .

When farmers adjust their portfolios, the two budget constraints are merged to form one single equation that determines the evolution of total wealth $m_t + a_t$. The value $F_t^1(s_t, i)$ is given by

$$F_t^1(s_t, i) = \max_{c_t, m_{t+1}, a_{t+1}} \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_t \left[\max_{j \in \{1, \dots, N\}} \{V_{t+1}(s_{t+1}, j) + \epsilon_{j,t+1}\} \right] \right\}, \quad (3.8)$$

$$\text{s.t. } m_{t+1} + a_{t+1} + c_t = m_t + (1 + r_t)a_t - \zeta_{i,t} + fZ_i - \kappa \mathbb{1}_{\{j \neq i\}}, \quad \text{with } c_t, m_{t+1}, a_{t+1} \geq 0,$$

where $\zeta_{i,t}$ is the portfolio adjustment cost in current market i .

If households choose to be workers, their value $W_t(s_t, i)$ is determined by solving a problem similar to the farmers', except that the subsistence income fZ_i is replaced with the equilibrium

²⁹The indicator function $\mathbb{1}_{\{j \neq i\}}$ equals 1 if households migrate at time t ; that is, market j where they live at time $t + 1$ is different from their current market i at time t .

local wage $w_{i,t}$ in market i . We present the worker problem in Online Appendix 3.1. In equilibrium, for each market i , $w_{i,t} \geq fZ_i$ must hold; otherwise, the local labor market in market i does not clear because households strictly prefer to be farmers than workers, resulting in no supply of labor. If $w_{i,t} > fZ_i$, households strictly prefer to be workers, and farmers do not exist in market i , whereas if $w_{i,t} = fZ_i$, households are indifferent to being workers or farmers. As a result, the supply of labor in market i is entirely determined by local entrepreneurs' demand for labor; households hired by entrepreneurs become workers and the remaining households that are not hired are farmers. Intuitively, this happens when market i is far from bank branches, where local entrepreneurs cannot run their businesses on a large scale because obtaining bank loans is too costly. This results in a low demand for labor and a low wage $w_{i,t}$ that is stuck at the subsistence level of income fZ_i . By reducing the credit entry cost $\psi_{i,t}$, bank expansion can generate local wage takeoffs across markets.

Finally, the value function of entrepreneurs is

$$E_t(s_t, i) = \max\{E_t^{00}(s_t, i), E_t^{10}(s_t, i), E_t^{01}(s_t, i), E_t^{11}(s_t, i)\}, \quad (3.9)$$

where the first superscript denotes whether entrepreneurs adjust (1) or do not adjust (0) their portfolios, and the second superscript denotes whether entrepreneurs borrow (1) or do not borrow (0). These values are determined recursively as follows. If entrepreneurs do not adjust their portfolios or borrow, their value is $E_t^{00}(s_t, i)$,

$$\begin{aligned} E_t^{00}(s_t, i) &= \max_{c_t, k_t, l_t, m_{t+1}} \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_t \left[\max_{j \in \{1, \dots, N\}} \{V_{t+1}(s_{t+1}, j) + \epsilon_{j,t+1}\} \right] \right\}, \quad (3.10) \\ \text{s.t. } m_{t+1} + c_t &= m_t - k_t + Z_i z_t (k_t^\alpha l_t^{1-\alpha})^{1-\nu} + (1-\delta)k_t - w_{i,t}l_t - \kappa \mathbb{1}_{\{j \neq i\}}, \\ k_t &\leq m_t, \\ a_{t+1} &= (1+r_t)a_t, \quad \text{with } c_t, m_{t+1} \geq 0. \end{aligned}$$

The above budget constraints imply that entrepreneurs use cash m_t to buy capital k_t , and the remaining $m_t - k_t$ earns no return. Profits are given by output $Z_i z_t (k_t^\alpha l_t^{1-\alpha})^{1-\nu}$ plus undepreciated capital $(1-\delta)k_t$ minus wage payments to workers $w_{i,t}l_t$.

If entrepreneurs adjust and borrow (which requires that $m_t \geq \psi_{i,t}$), their value is $E_t^{11}(s_t, i)$:

$$E_t^{11}(s_t, i) = \max_{c_t, k_t, l_t, m_{t+1}, a_{t+1}} \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_t \left[\max_{j \in \{1, \dots, N\}} \{V_{t+1}(s_{t+1}, j) + \epsilon_{j,t+1}\} \right] \right\}, \quad (3.11)$$

$$\begin{aligned} \text{s.t. } m_{t+1} + a_{t+1} + c_t &= -[1 + (r_t + \chi)\mathbb{1}_{\{k_t \geq m_t\}}][k_t - (m_t - \psi_{i,t})] + (1 + r_t)a_t \\ &\quad - \zeta_{i,t} + Z_i z_t (k_t^\alpha l_t^{1-\alpha})^{1-\nu} + (1 - \delta)k_t - w_{i,t}l_t - \kappa \mathbb{1}_{\{j \neq i\}}, \\ k_t &\leq (m_t + a_t - \psi_{i,t})/\xi, \quad \text{with } c_t, m_{t+1}, a_{t+1} \geq 0, \end{aligned}$$

where $\mathbb{1}_{\{k_t \geq m_t\}}$ is an indicator function that equals 1 if $k_t \geq m_t$. Entrepreneurs choose to borrow only when they want to use an amount of capital k_t that exceeds their own cash m_t . In this case, they borrow $k_t - (m_t - \psi_{i,t})$ from the bank at the lending rate $r_t + \chi$. The other two cases $E_t^{10}(s_t, i)$ and $E_t^{01}(s_t, i)$ can be formulated similarly, and their formulations are relegated to Online Appendix 3.1.

We elucidate the model mechanisms by presenting households' choice of occupations, loans, portfolio composition (cash/deposits), and migration in Online Appendix 3.3.

Equilibrium Migration Flows. Among households of type $s_t = \{z_t, m_t, a_t\}$ in market i at time t , a fraction $\omega_{i',t}(s_t, i)$ will migrate to market i' at time $t + 1$ (see Online Appendix 3.2 for the derivation):

$$\omega_{i',t}(s_t, i) = \mathbb{E}_t \left[\frac{\exp(V_{t+1}(s_{t+1}, i'))^{1/\eta}}{\sum_{j=1}^N \exp(V_{t+1}(s_{t+1}, j))^{1/\eta}} \middle| s_t, i \right], \quad (3.12)$$

where $\mathbb{E}_t[\cdot]$ is taken with respect to z_{t+1} .³⁰

Equation (3.12) clearly shows that households are more likely to migrate to markets that offer higher values V_{t+1} in equilibrium than other markets. A higher fixed migration cost κ implies that households will obtain lower values after migrating to other markets $i' \neq i$ (due to a lower m_{t+1}), which reduces the equilibrium migration rate. The impact of idiosyncratic taste shocks $\{\epsilon_{j,t+1}\}_{j=1}^N$ is sufficiently summarized by the scale parameter η . A larger η increases the importance of taste shocks in determining the move. For example, as η goes to ∞ , each individual household's migration decision becomes completely random and the proportion of households going to each market is simply $1/N$. In general, household type s_t and market characteristics (i.e., $\Pi_{i,t}$, Z_i , $d_{i,t}$) jointly determine households' occupation choice, credit access, and portfolio adjustment decisions, which in turn determine the evolution of m_{t+1} , a_{t+1} and the values that households obtain in different markets. As a result, there is significant heterogeneity in household migration decisions,

³⁰Cash m_{t+1} and deposits a_{t+1} are determined by the budget constraints described for the household problem.

which we discuss in Online Appendix 3.3.4.

Using equation (3.12), the continuation value in the household problem ((3.6), (3.8), (3.10), (3.11)) can be simplified to:

$$\mathbb{E}_t \left[\max_{j \in \{1, \dots, N\}} \{V_{t+1}(s_{t+1}, j) + \epsilon_{j,t+1}\} \right] = \mathbb{E}_t \left[\eta \log \left(\sum_{j=1}^N \exp(V_{t+1}(s_{t+1}, j))^{1/\eta} \right) \right], \quad (3.13)$$

where $\mathbb{E}_t[\cdot]$ on the right-hand side is taken with respect to z_{t+1} . Online Appendix 3.2 provides the derivation.

3.3 Bank Expansion

The number of branches opened in each period $t \geq 1$ is n_t , which is exogenously determined from the data (see our calibration in Section 4). For tractability, instead of considering a decentralized equilibrium with many small banks, we focus on the central authority's problem of determining the locations of new branches. At the very beginning $t = 0$, given the existing branches Ψ_0 , the central authority chooses the locations of all new branches opened in each period $t \geq 1$ to maximize total profits,

$$\max_{\{\Lambda_t\}_{t=1}^{\infty}} \sum_{t=1}^{\infty} \left(\sum_{i \in \Lambda_t} \Theta_{i,t} \right) + \sum_{i \in \Psi_0} \Theta_{i,0} \quad (3.14)$$

$$\text{s.t. } \Lambda_t \subset \Psi_{t-1}^C \text{ and } |\Lambda_t| = n_t \text{ for all } t \geq 1, \quad (3.15)$$

$$\Psi_t = \Psi_{t-1} \cup \Lambda_t \text{ for all } t \geq 1, \quad (3.16)$$

where the first term in the objective function (3.14) represents the profits of new branches opened at time $t \geq 1$ and the second term represents the profits of branches in Ψ_0 , which already exist at time $t = 0$. The variable $\Theta_{i,t}$ is the present value of future profits generated by a branch opened in market i at time t (see equation (3.17)). The choice variable $\{\Lambda_t\}_{t=1}^{\infty}$ represents the set of markets where new branches are opened in each period $t \geq 1$. Constraint (3.15) indicates that n_t new branches are opened at time t , whose locations are selected from the set of markets without branches at time $t - 1$.³¹ Constraint (3.16) determines the evolution of the set of markets with branches over time. Thus, given $\{n_t\}_{t=1}^{\infty}$, the optimal location choice for new branches boils down to solving a combinatorial dynamic programming problem (3.14).

Next, we derive the present value of profits $\Theta_{i,t}$ generated by a branch opened in market i at time t . A branch makes profits by lending to entrepreneurs at the rate $r_t^l = r_t + \chi$, which is higher

³¹The set Ψ_{t-1}^C is the complement of Ψ_{t-1} , i.e., $\Psi_{t-1}^C = \mathcal{C} \setminus \Psi_{t-1} = \{i : B_{i,t-1} = 0, i \in \mathcal{C}\}$ and $|\cdot|$ denotes the cardinality of a set.

than the interest rate r_t by a markup χ . Thus, the net profit per unit of loans is $\chi = r_t^l - r_t$.³² The present value of the profits that the branch generates for $t' \geq t$ is given by

$$\Theta_{i,t} = \chi \sum_{t'=t}^{\infty} \beta^{t'} \left[X_{i,t'} + \sum_{j \in \{j: d_{j,t'} = \tau_{ij}\}} X_{j,t'} \right]. \quad (3.17)$$

In equation (3.17), the total amount of loans made by the branch opened in market i have two components. First, the term $X_{i,t'}$ captures the loans offered to local entrepreneurs in market i at time t' , defined in equation (3.19). The term $\sum_{j \in \{j: d_{j,t'} = \tau_{ij}\}} X_{j,t'}$ captures loans due to spatial spillovers, i.e., loans to entrepreneurs from nearby markets without branches who travel to market i to borrow. These markets are identified by the set $\{j : d_{j,t'} = \tau_{ij}\}$, meaning that their distance from the nearest bank branch at time t' , $d_{j,t'}$, is equal to their distance from market i , τ_{ij} . The set $\{j : d_{j,t'} = \tau_{ij}\}$ may shrink over time if future branch openings lead to $d_{j,t'}$ falling below τ_{ij} for some market j . As we show in Online Appendix 3.7.2, because branch locations are chosen to maximize profits (equation (3.14)), branches tend to be opened in markets with higher $\Pi_{i,t}$, higher Z_i , or in markets that can serve households in nearby markets.

One way to interpret problem (3.14) is that the locations of new branches are determined under the auspices of the central bank licensing board, as if it is a coordinating, profit-maximizing monopoly. This modeling specification is helpful computationally, as the strategy space increases tremendously if we assume that branches are owned by different small banks that compete with each other in a dynamic game.³³ Although we focus on the allocation by the central authority mainly for computational tractability, this specification does reflect, to some extent, the nature of the commercial banking sector in Thailand during our study period. Beng (1994) documents that the Thai commercial banking sector during our period of interest was highly concentrated, being dominated by a few large banks; indeed, in 1981, the top three largest banks controlled 60% of the industry's total assets. Moreover, government interests were prevalent in this sector. For instance, the Thai government held more than 90% of the shares in the second

³²Our implicit assumption is that the per-unit cost of funds is the same for all branches and is equal to the interest rate r_t . This assumption essentially means that the interbank offered rate across branches located in different markets is the same as the deposit rate offered to households. Although the lack of historical data means that we do not know the interbank rate for the 1986-1996 period, recent data indicate that our assumption is reasonable. In 2005, the Bank of Thailand introduced the Bangkok Interbank Offered Rate (BIBOR), which is a forward-looking interest rate benchmark that reflects the local Thai baht market. Data from the Bank of Thailand and the World Bank Development Indicators show that over 2005-2020, the average 1-year deposit rate offered to individuals and corporations was 1.88%, whereas the loan rate was 4.84%. The average 1-year interbank rate was 2.55%, which, although not identical, is reasonably close to the average 1-year deposit rate.

³³For example, consider the case in which n branches are chosen from N locations. If the locations of these branches are chosen jointly with the central authority to maximize total profits, there are $\binom{N}{n} = \frac{N!}{(N-n)!n!}$ possible combinations. If the locations of these branches are chosen sequentially by n different banks, as in a Nash equilibrium of sequential game, there are $\prod_{i=1}^n \binom{N-i+1}{1} = \frac{N!}{(N-n)!}$ possible combinations.

largest commercial bank, Krung Thai Bank, and substantial interests in numerous other banks (Skully, 1984). Given the high concentration and government ownership in this sector, it is likely that there was a certain degree of coordination, under the guidance of the government, between commercial banks in their branch expansion. In a recent study, Assuncao, Mityakovy and Townsend (2020) document that BAAC deliberately yields ground to the expansion of the commercial banking sector in Thailand. Such anti-preemptive behavior can be partly rationalized in their model by assuming that BAAC considers joint profit maximization in choosing branch locations. Assuncao, Mityakovy and Townsend (2020) show that their baseline oligopoly model implies similar patterns of financial access as the one with a single monopolistic financial provider. Although the oligopolistic competition that they model may provide a more realistic description of the Thai banking sector than our simple monopoly specification, our model would become intractable if we consider dynamic oligopolies with a large number of markets.³⁴

As noted for equation (3.17), branches have spatial spillovers to nearby markets without branches. The spatial spillovers naturally imply cannibalization across branches as new branch openings may attract households who are already served by existing branches. When solving problem (3.14), the central authority is forward looking and internalizes such spatial spillovers and cannibalization across branches, not only for branches opened in the same periods but also for those opened in different periods. Needless to say, the central authority internalizes the general equilibrium effects of new branch openings on interest rates and wages. Thus, the location choice problem in our model is more complicated than the static problem solved by Jia (2008).

Spatial spillovers and cannibalization across branches make the combinatorial dynamic programming problem (3.14) NP-hard and impossible to solve exactly, given the large number of markets in our model. Therefore, we propose a tractable numerical algorithm that solves the problem approximately in polynomial time (see Online Appendix 5). In brief, we break the location choice of branches across the country into a set of smaller problems that focus on specific segments of the country. These segments are constructed using the k -medoids clustering algorithm in machine learning to ensure that there is little interaction among locations belonging to different segments. This allows us to solve the problem of each segment separately, which is computationally feasible. Finally, we solve the whole country’s bank expansion problem by aggregating all segments’ location choices and transforming the problem into a tractable multidimensional multiple-choice knapsack problem.

³⁴To maintain tractability, Assuncao, Mityakovy and Townsend (2020) apply their oligopoly model to 10 selected provinces, which have a small number of markets and less than six entry episodes. Moreover, in contrast with our model, they do not consider heterogeneous forward-looking households within each market. In Online Appendix 3.8, we conduct robustness checks and show that modeling a more competitive banking sector does not greatly change the main quantitative predictions of the model.

3.4 Equilibrium and Aggregation

Figure 4 presents the circular flow of our model to facilitate discussion of the equilibrium. Denote by $\phi_t(s|i)$ the probability density function of households of type $s = \{z, m, a\}$ in market $i \in \mathcal{C}$ at time $t \geq 0$. Given the initial distribution and market size $\{\phi_0(s|i), \Pi_{i,0}\}_{i=1}^N$ at $t = 0$, and the number of new branch openings n_t at $t \geq 1$, the competitive equilibrium consists of the choice of new branch locations Λ_t for $t \geq 1$, consumption $c_t(s, i)$, savings in the form of cash $m_{t+1}(s, i)$ and deposits $a_{t+1}(s, i)$, migration decisions, occupations, credit access, portfolio choices, capital $k_t(s, i)$, and labor $l_t(s, i)$ for each household of type s in each market $i \in \mathcal{C}$, sequences of the distribution of households $\phi_t(s|i)$, market size $\Pi_{i,t}$ and wage $w_{i,t}$ for each market $i \in \mathcal{C}$, and the interest rate r_t for all $t \geq 0$, such that the following conditions are satisfied.

- (i). Given $\{\Psi_\tau, r_\tau\}_{\tau=0}^\infty$ and $\{\phi_\tau(s|i), \Pi_{i,\tau}, w_{i,\tau}\}_{\tau=0}^\infty$ for $i \in \mathcal{C}$, households of type s in market i choose $c_t(s, i)$, $a_{t+1}(s, i)$, $m_{t+1}(s, i)$, whether to migrate, their occupations, credit access, portfolio adjustments, $k_t(s, i)$, and $l_t(s, i)$ optimally by solving problems (3.5) to (3.11) for all $t \geq 0$.
- (ii). Given $\{r_\tau\}_{\tau=0}^\infty$, $\{n_\tau\}_{\tau=1}^\infty$, $\{\phi_\tau(s|i), \Pi_{i,\tau}, w_{i,\tau}\}_{\tau=0}^\infty$ for $i \in \mathcal{C}$, and the evolution of households' variables, the choice of new branch locations Λ_t for $t \geq 1$ solves problem (3.14).
- (iii). The equilibrium interest rate r_t is determined by the economy-wide loan-market clearing condition at time t :

$$\sum_{i=1}^N \Pi_{i,t} \int a \phi_t(s|i) ds = \sum_{i=1}^N X_{i,t}, \quad (3.18)$$

where the left-hand side is the supply of loans from household deposits. The right-hand side is the demand for loans from entrepreneurs, where the demand in market i is given by

$$X_{i,t} = \Pi_{i,t} \int [k_t(s, i) - (m - \psi_{i,t})] \mathbb{1}_{\{k_t(s, i) \geq m\}} \phi_t(s|i) ds, \quad (3.19)$$

In Online Appendix 4.6, we present the model's implications for the flow of funds across markets.

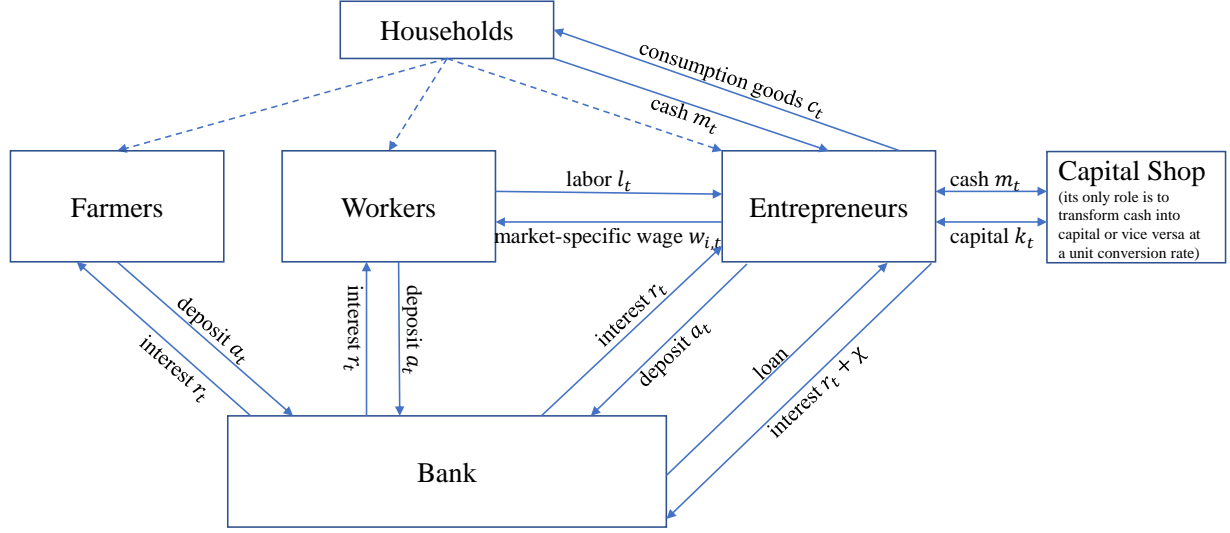
- (iv). The equilibrium wage $w_{i,t}$ in each market $i \in \mathcal{C}$ is determined by taking into account two cases. If the demand for workers $\int l_t(s, i) \phi_t(s|i) ds$ is lower than the measure of non-entrepreneurs $\int \mathbb{1}_{\{V_t(s, i) > E_t(s, i)\}} \phi_t(s|i) ds$ in market i , we have $w_{i,t} = fZ_i$. Otherwise, we have $w_{i,t} > fZ_i$, and the local wage $w_{i,t}$ is determined by the labor-market clearing condition in market i :

$$\int \mathbb{1}_{\{V_t(s, i) > E_t(s, i)\}} \phi_t(s|i) ds = \int l_t(s, i) \phi_t(s|i) ds. \quad (3.20)$$

- (v). The size of each market $i \in \mathcal{C}$ evolves according to migration flow equation (3.12):

$$\Pi_{i,t+1} = \sum_{j=1}^N \Pi_{j,t} \int \omega_{i,t}(s, j) \phi_t(s|j) ds, \quad (3.21)$$

A. Circular flow of the aggregate economy



B. Circular flow across local spatial markets

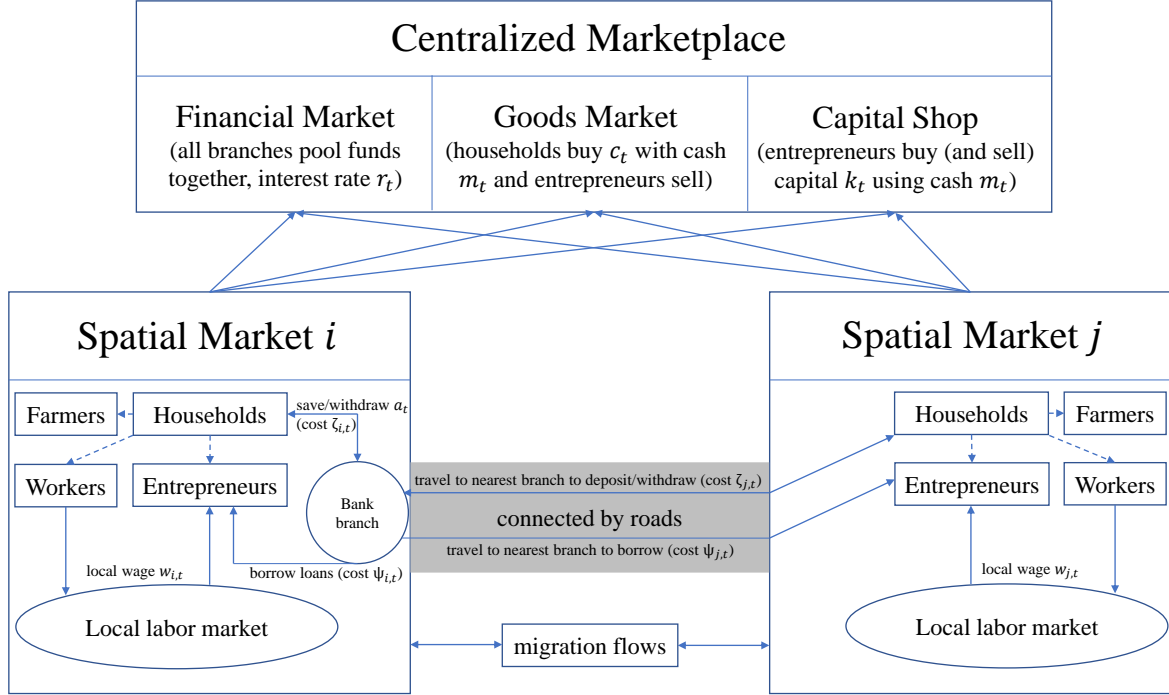


Figure 4: Circular flow of the model.

which includes households $(\sum_{j \neq i} \Pi_{j,t} \int \omega_{i,t}(s, j) \phi_t(s|j) ds)$ who live in other markets $(j \neq i)$ at time t but choose to migrate to market i at time $t + 1$, and households $(\Pi_{i,t} \int \omega_{i,t}(s, i) \phi_t(s|i) ds)$ who live in market i at time t and choose to stay in market i at time $t + 1$.

(vi). The distribution of households $\phi_t(s|i)$ in each market $i \in \mathcal{C}$ evolves according to the equilibrium decisions of households and the allocation of quantities and prices.

(vii). The set Ψ_t , consisting of markets with branches, evolves according to equation (3.16).

4 Calibration

Each period represents 1 year. The model begins at time $t = 0$, which corresponds to 1986. We calibrate the initial locations of the 406 branches in 1986 directly according to the data. Bank expansion starts from time $t = 1$ (i.e., 1987) and ends at time $t = 10$ (i.e., 1996).³⁵ The number of new branches n_t opened in each year between 1987 and 1996 is specified exogenously according to the data (panel A of Figure 6).

Below, we first calibrate the characteristics of the local spatial markets for the initial year, 1986, in Subsection 4.1. We then calibrate the model's parameters, which are either determined from external information without simulating the model (Subsection 4.2) or calibrated internally from moment matching (Subsection 4.3). Finally, in Subsection 4.4, we validate the model-implied dynamic effects of branch openings at the market level against our empirical estimates in Table 1.

4.1 Market Heterogeneity

Figure OA.3 in Online Appendix 1.2 displays the values for the three dimensions of market heterogeneity, $\Pi_{i,t}$, $d_{i,t}$, and Z_i , which are calibrated as follows.

The population for each market is the sum of the village and municipal populations in the data (see Online Appendix 1.2). For each $i \in \mathcal{C}$, we calibrate market size $\Pi_{i,0}$ at time $t = 0$ according to the estimated market-level population density in 1986.³⁶ The evolution of $\Pi_{i,t}$ for $t > 0$ is determined by equation (3.21).

The distance τ_{ij} between markets $i, j \in \mathcal{C}$ is measured by the car travel time between the two markets along the road network using our GIS data. Branch locations evolve over time according to equation (3.16). Given branch locations in each year t and τ_{ij} for $i, j \in \mathcal{C}$, the distance from the nearest branch $d_{i,t}$ for each market $i \in \mathcal{C}$ is computed according to equation (3.1).

³⁵To ensure the existence of a steady state and consistency with the branch locations in 1996, we assume that no new branches are opened after 1996. In Online Appendix 4.7, we verify that allowing new branches to continue to open for the 1997-2011 period according to the data has a negligible impact on the transitional dynamics for our period of interest, 1986-1996.

³⁶In the model, each market is represented by a single node (panel B of Figure 2), so each occupies the same "area." However, the market area differs across markets in the data (panel A of Figure 2). Thus, population density is a better measure of market size than population because it adjusts for heterogeneous market areas in the data.

Finally, we calibrate market-specific productivity Z_i . In our model, Z_i captures cross-market differences in income per capita that are not explained by differences in capital stock or access to bank branches. Therefore, we run the following cross-sectional regression using the CDD data in 1986:

$$\ln(Y_i) = \alpha + \beta_1 \ln(K_i) + \beta_2 B_i + \epsilon_i, \quad (4.1)$$

where $\ln(Y_i)$ and $\ln(K_i)$ are the log income per capita and log capital stock per capita of market i ; B_i is a dummy variable indicating whether market i has a branch in 1986. The predicted value $\exp(\hat{\beta}_1 \ln(K_i) + \hat{\beta}_2 B_i)$ reflects the cross-market variation in income per capita due to variations in K_i and B_i . Thus, the residual value $\hat{\mu}_i = \exp(\hat{\alpha} + \hat{\epsilon}_i)$ is informative about market-level productivity shifters.³⁷ We sort $\hat{\mu}_i$ into quintiles and compute the mean of each quintile, denoted by $\hat{\mu}(Q_k)$ for $k = 1, 2, \dots, 5$.

Turning to the model, to maintain tractability, we assume that Z_i can take five possible values, $\{H_k\}_{k=1}^5$. For each market $i \in \mathcal{C}$, we calibrate productivity at $Z_i = H_k$ if the market is in the k th quintile. We calibrate $\{H_k\}_{k=1}^5 = \{0.84, 0.92, 0.99, 1.09, 1.29\}$ to ensure that relative differences in productivity across quintiles in the model are consistent with those in the data, namely, $H_k/H_{k-1} = \hat{\mu}(Q_k)/\hat{\mu}(Q_{k-1})$ for $k = 2, 3, \dots, 5$; and average productivity in 1986 is (normalized to) unity, i.e., $\bar{Z} \equiv \sum_{i=1}^N Z_i \Pi_{i,0} / \sum_{i=1}^N \Pi_{i,0} = 1$.³⁸

4.2 Externally Determined Parameters

The interest rate spread is set at $\chi = 4.82\%$ according to the average value of the difference between the prime lending rate and the interest rate provided by the Bank of Thailand for the 1986-1996 period. Following standard practice, we set the risk aversion parameter at $\sigma = 1.5$. We set the production technology parameters at $\alpha = 0.33$ and $\nu = 0.14$ according to the estimates of Paweenawat and Townsend (2019) using the Townsend Thai data. The 1-year depreciation rate δ is set at 0.08, following Samphantharak and Townsend (2009). We set the capacity of bank branches h at 150 people/km², corresponding to the median population density across all markets. We study the role of h in Online Appendix 3.7.3.

³⁷As in Acemoglu and Dell (2010), we include $\hat{\alpha}$ in the residual value but not in the predicted value because it reflects the overall productivity. Regression specification (4.1) is in spirit similar to that of Acemoglu and Dell (2010); in their model, region-specific productivity is captured by the residual component of labor income, which is empirically estimated in a cross-sectional regression that controls standard individual characteristics correlated with labor income.

³⁸To clarify the role of productivity heterogeneity in driving the model's quantitative implications, we solve an alternative model specification in which all markets have the same productivity levels in Online Appendix 4.3.1. We show that the local and aggregate impacts of branch openings are much larger than those in our baseline model with productivity heterogeneity across markets. One main reason is that, according to our estimates, markets with bank branches in 1986 tend to be more productive than other markets. Thus, the initial level of GDP in 1986 is higher when markets exhibit productivity heterogeneity, which naturally lowers the GDP growth rate in subsequent years.

Table 2: Calibration and parameter choice.

Panel A: Externally determined parameters					
Parameter	Symbol	Value	Parameter	Symbol	Value
Risk aversion	σ	1.5	Capital share	α	0.33
Return to scale	ν	0.14	Depreciation rate	δ	0.08
Interest rate spread (%)	χ	4.82	Branch capacity	h	150
Panel B: Internally calibrated parameters					
Parameter	Symbol	Value	Moments	Data	Model
Discount rate	β	0.89	Interest rate in 1986	8.3%	8.3%
Subsistence income	f	0.77	Fraction of farmers in 1986	46%	46%
Fixed migration cost	κ	2.2	Migration rate, 1986-1996	4.7%	4.7%
Idiosyncratic taste dispersion	η	0.008	Out-migrant share ratio	0.89	0.89
Portfolio adj. cost	ζ	0.1	Average deposit-cash ratio	27%	27%
Sensitivity of $\zeta_{i,t}$ to distance	θ_ζ	0.0015	Sensitivity of deposit-cash ratio to $d_{i,t}$	-1.07%	-1.05%
Credit entry cost	ψ	0.83	Frac. of households with loans	1.63%	1.63%
Sensitivity of $\psi_{i,t}$ to distance	θ_ψ	0.215	DID estimate ($\hat{\alpha}_0$) for credit access	0.034	0.031
Liquidation loss rate	ξ	0.59	DID estimate ($\hat{\alpha}_0$) for employment	0.186	0.196
Tail of talent distribution	ρ	4.7	std($\Delta \log(\text{revenue})$)	0.58	0.58
Persistence of talent	γ	0.72	AC1 of $\log(\text{revenue})$	0.86	0.88
			AC3 of $\log(\text{revenue})$	0.77	0.73
			AC5 of $\log(\text{revenue})$	0.71	0.63

4.3 Internally Calibrated Parameters

The remaining parameters are calibrated by matching relevant moments. We first solve and simulate the entire transition path for the 1986-1996 period. We then calculate the model-implied moments and adjust the parameters until these moments are in line with their values in the data. Although most of the moments that we target are in the initial year, 1986, the whole transition path needs to be solved again whenever parameters are changed because households are forward looking. We specify that the economy is in a steady state (without migration) in 1986, following standard practice (e.g., Buera and Shin, 2013; Herkenhoff, 2019; Kaplan, Mitman and Violante, 2020). The remaining parameters are determined jointly, as each moment is affected by every parameter. Below, we make a heuristic identification argument that relates each parameter to the moment that intuitively determines it.

The initial interest rate in 1986 is 8.3% in the data, and we calibrate the discount rate $\beta = 0.89$ to match it. The parameter f determines the level of subsistence income, and we calibrate $f = 0.77$ to match the fraction of farmers in 1986, which is 46% in the data.

Individual Talent Process. The parameters γ and ρ govern the persistence and variation of individual talent, respectively, which determine the revenue generated by household assets. We set these two parameters at $\gamma = 0.72$ and $\rho = 4.7$ so that the overall dynamics of households' asset-generated revenue implied by the model are consistent with those in the Townsend Thai annual survey. We choose four moments to capture the dynamics of asset-generated revenue, including the standard deviation of log revenue growth and the autocorrelation of log revenue with horizons of 1, 3, and 5 years. In the model, asset-generated revenue is defined as households' interest income from deposits plus revenue from their businesses (for those who are entrepreneurs). As in the data, labor income is excluded because it is not generated by assets (Samphantharak and Townsend, 2018). In Online Appendix 4.3.4, we discuss the sensitivity of our model's quantitative implications to these two parameters.

Migration Costs. We choose the values of the two parameters κ and η to match the migration flows in the Thai data. For each village, the CDD data document the number of people working outside the township in each survey year. These people are considered out-migrants of the township. By aggregating the out-migrants and populations across all villages, we construct the out-migrant share (i.e., the number of out-migrants divided by the population) in each survey year at the country level (see Online Appendix 1.3). Similar to Munshi and Rosenzweig (2016) and Tombe and Zhu (2019), we estimate a migration rate of 4.7% based on the increase in the out-migrant share over the 1986-1996 period.³⁹ In addition, we estimate that the average ratio of the share of out-migrants in markets with branches to that in markets without branches is 0.89 for 1986-1996, indicating that a smaller fraction of households living in markets with branches choose to migrate to other markets.

Although parameters κ and η both affect the equilibrium migration flows implied by the model, their roles differ. The fixed migration cost κ directly determines the migration decisions of households of different types and thus this parameter is calibrated to match the overall migration rate for the 1986-1996 period. The parameter η determines migration decisions for idiosyncratic

³⁹A similar migration rate is documented by Townsend (2011). In response to any concerns that the migration rate appears to be low, we make three comments. First, the out-migrant share that we construct using the data captures the number of out-migrants at the township level. Migration in Thailand is mostly (but not entirely) local, involving people moving from one village to another. Second, in our model, the smallest geographic unit is the market of 3-8 townships, as defined in Section 2.2. Thus, the actual cross-market migration rate can be even lower in the data than in our estimate. Third, low migration rates are also observed in other developing countries. For example, Munshi and Rosenzweig (2016) document that the rural-urban migration rate of working-age men in India was less than 2% between 1982 and 1991 despite the large rural-urban wage gap. They argue that the low migration rate can be attributed to the tradeoff between caste-based rural insurance networks and income gains from migration. Morten (2019) develops a model to study the joint determination of temporary migration and risk sharing in rural India, where permanent migration is very low. In other developing countries, the rural-urban migration rate is much higher than in India or Thailand. For instance, in Brazil, the 1997 Brazil Demographic and Health Survey finds a rural-urban migration rate of 13.9% (Munshi and Rosenzweig, 2016).

reasons. In Figure OA.23 in Online Appendix 4.1.1, we show that a higher η increases the share of out-migrants more (less) in markets with (without) branches. Thus, the parameter η is calibrated to match the ratio of out-migrant share for markets with versus markets without branches.

Credit Entry and Portfolio Adjustment Costs. Because $\psi_{i,t}$ and $\zeta_{i,t}$ are not directly observable, we calibrate their values through parametric indirect inference. We assume that both $\psi_{i,t}$ and $\zeta_{i,t}$ are linear functions of $d_{i,t}$, $\psi_{i,t} = \psi + \theta_\psi d_{i,t}$ and $\zeta_{i,t} = \zeta + \theta_\zeta d_{i,t}$.⁴⁰ We specify different sensitivity parameters, θ_ψ and θ_ζ , for the two costs because as discussed in Section 3.2, $\psi_{i,t}$ reflects information costs but $\zeta_{i,t}$ does not. The parameters ψ and ζ determine the overall costs of obtaining credit access and adjusting portfolios. We calibrate their values at $\psi = 0.83$ and $\zeta = 0.1$ so that the model-implied average fraction of households with loans is 1.63% and the average household deposit-cash ratio is 27%, as in the data.⁴¹

The parameter θ_ψ determines the change in credit entry costs due to branch expansion. Thus, the effect of branch openings on credit access is informative about its value. Specifically, we implement the DID method in specification (2.1) in the simulated data to estimate the causal impact of branch openings on the local fraction of households with bank loans (see Section 4.4). We calibrate $\theta_\psi = 0.215$ so that the model-implied 2-year impact aligns with the estimate in the data ($\hat{\alpha}_0$ in column (4) of Table 1). In Online Appendix 4.3.3, we show that choosing a higher θ_ψ will increase the model-implied impact, making it inconsistent with that in the data.

One informative moment for identifying the parameter θ_ζ is the impact of branch openings on local households' deposit-cash ratios. However, we do not have a DID estimate for this effect because the CDD data do not provide information on households' deposits or cash. Thus, to help calibrate this parameter, we use the Townsend Thai monthly surveys. In Table OA.8 in Online Appendix 2.3, our panel regression estimates that a 1-minute increase in car travel time is associated with a 1.07% decrease in the deposit-cash ratio. Thus, we calibrate $\theta_\zeta = 0.0015$ so that the regression coefficient in the simulated data is similar. To mitigate omitted variable bias, we provide an extensive robustness check for different values of parameter θ_ζ in Online Appendix

⁴⁰We are conscious that the functional forms of $\psi_{i,t}$ and $\zeta_{i,t}$ can affect the quantitative implications of bank expansion in our model. However, nonparametrically estimating the relationships between access to bank loans, bank deposits, and distance from the nearest branch requires detailed household data. It is more difficult to identify more flexible functional forms due to the larger number of parameters. In the absence of such high-quality data, a linear functional form is a natural and simple initial benchmark. The quantitative implications are unlikely to vary much so long as the model is calibrated to match the same DID estimates.

⁴¹In our model, households who borrow from banks are entrepreneurs. On average, their income and loan amounts are 9.89 and 15.6, respectively, and they pay a credit entry cost $\psi_{i,t}$ of 0.98. On average, households who hold deposits have income and consumption amounts of 1.39 and 1.38, respectively, and they pay a portfolio adjustment cost of 0.11. Thus, our calibration suggests that households pay about 8%-10% of their income to access bank deposits or loans. The magnitude of these costs seems high because both costs are implicitly "catch-all" variables to capture the high barriers to financial access in the data. Large calibrated costs are not uncommon in the literature: for example, Townsend and Ueda (2006, footnote 39) calibrate the fixed cost of entry into formal financial systems in Thailand in 1976 as one-third of household wealth to match the low credit access ratio.

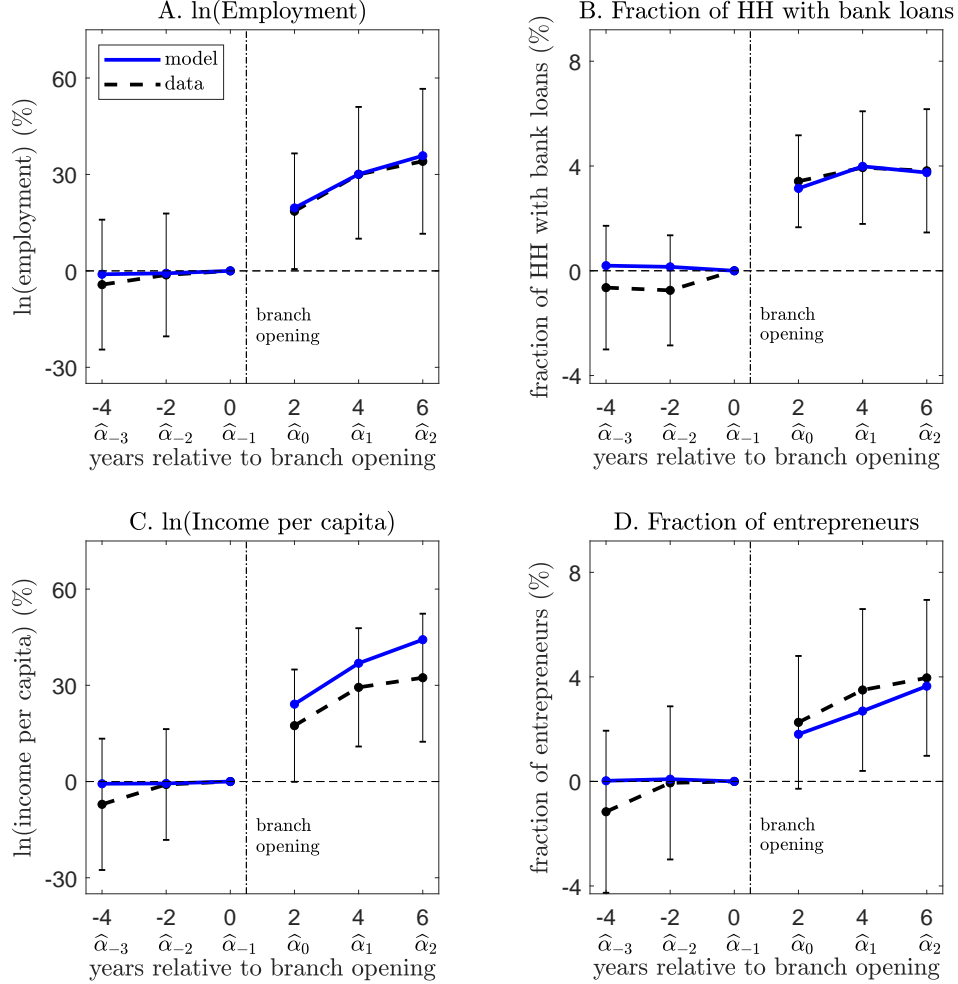
4.2.2. We show that alternative calibrations of $\theta_\zeta = 0$ (so that distance $d_{i,t}$ does not affect $\zeta_{i,t}$) or $\theta_\zeta = \theta_\psi$ (so that distance $d_{i,t}$ has the same effect on $\psi_{i,t}$ and on $\zeta_{i,t}$) generate very similar quantitative implications of bank expansion, although the relative importance of the underlying credit and deposit channels varies.

Collateral Constraints. The parameter ξ determines the amount of loans that households can borrow once they can access credit. Thus, one informative moment for identifying the value of ξ is the increase in the amount of bank loans after branch openings. Unfortunately, however, our CDD data do not provide loan amounts. According to our model, entrepreneurs borrow to buy capital, which increases the demand for labor, owing to the complementarity between capital and labor in production. Thus, changes in local employment after branch openings can reflect changes in loan amounts. Therefore, we calibrate the value of ξ so that the model-implied 2-year impact of branch openings on employment based on the DID specification (2.1) aligns with the estimate in the data ($\hat{\alpha}_0$ in column (1) of Table 1). The calibrated value of $\xi = 0.59$ implies that the median loan-collateral ratio among entrepreneurs with credit access is about 0.54 in our model, which is reasonably close to the value of 0.59 in the 1997 Townsend Thai annual survey, after excluding unsecured loans with no collateral requirements. In Online Appendix 4.3.3, we show that choosing a lower ξ will significantly increase the effects of branch openings on local employment and income per capita, making the model-implied DID estimates inconsistent with those from the data.

4.4 Model Validation for Market-Level Impacts of Branch Openings

As one of our model validation exercises, we compare the model-implied market-level impacts of branch openings with the DID estimates in the data. Specifically, we run the same DID estimation according to specification (2.1) using simulated data, where treatment and control markets are matched by their propensity scores. When estimating propensity scores, we use covariates $\Pi_{i,t}$, $d_{i,t}$, and Z_i , which fully summarize market heterogeneity in our model.

Figure 5 compares the market-level effects of branch openings in the model (blue solid lines) and data (black dashed lines). Our calibration in Section 4.3 only targets the two point estimates, $\hat{\alpha}_0$, in panels A and B, corresponding to the 2-year effects of branch openings on local employment and credit access. Nevertheless, the model-implied effects are reasonably close to the empirical DID estimates for all leads and lags, despite the match not being perfect. Panels C and D show that the model-implied effects of branch openings on local income per capita and the fraction of entrepreneurs are also reasonably close to the DID estimates in the data, although these two variables are not our targets in the calibration. The model implies larger effects on income per capita and smaller effects on the fraction of entrepreneurs compared with the data, but the



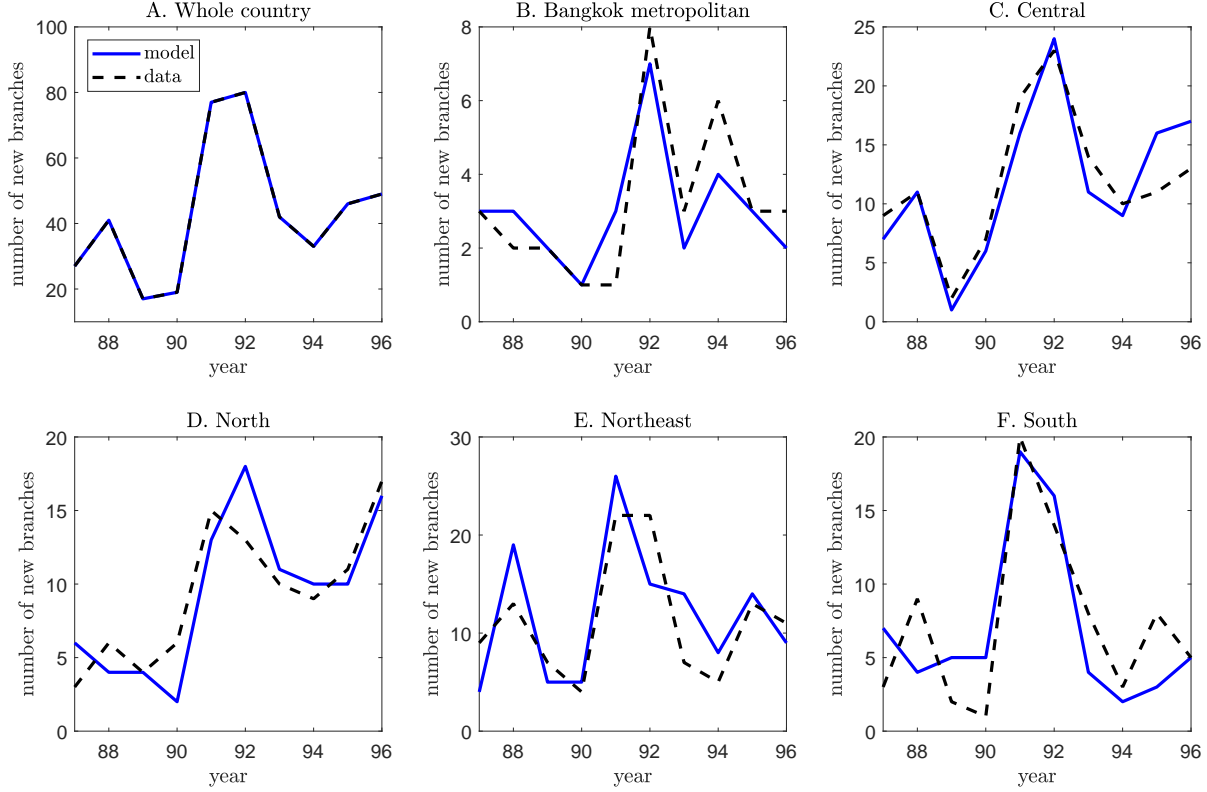
Note: The black dashed lines visualize the empirical estimates in Table 1, in which all coefficients are normalized relative to $\tau = -1$. The vertical bars represent the corresponding 95% confidence intervals. The blue solid lines represent the model-implied DID estimates in the simulated data. The vertical dash-dotted line indicates that a branch is opened at some point between year $t = 0$ and year $t = 2$.

Figure 5: Dynamic effects of branch openings at the market level.

differences are within the 95% confidence intervals of the empirical estimates.

5 Model Prediction on Branch Locations

In this section, we examine the model's predictions on the placement of 431 new branches opened during the 1987-1996 period. Of the 1,428 markets defined in Section 2.2, 406 markets already had branches in 1986 and 1,022 did not. Our model focuses on predicting the locations of the 431 new branches from among these 1,022 markets without branches in 1986. In Subsection 5.1, we first study the model's ability to capture the overall geographic patterns of new branch



Note: Panel A illustrates that our calibration exogenously specifies the number of new branches opened each year in the whole country. Panels B-F compare the number of new branches opened in different regions. The total number of branches opened in each region in the model and data, respectively, are as follows: Bangkok: 30, 32; central: 118, 119; north: 94, 94; northeast: 119, 113; and south: 70, 73. For details, see Table OA.11 in Online Appendix 3.7.5.

Figure 6: Branches opened in different regions, 1987-1996.

openings and in Subsection 5.2, we evaluate the model's predictive power for the locations of these branches, elucidating the relative importance of each market characteristic.

5.1 Geographic Patterns of Branch Expansion

In the data, the new branches opened each year are spread over the entire country, and, in general, the branches are not close to each other. Thus, the expansion of bank branches during our study period in Thailand does not appear to begin at a certain point and radiate from this center outward. Instead, banks tend to open branches in places that are distant from existing branches (see Online Appendix 3.7.4).

This spatial diffusion pattern for bank branches is very different from that of retail businesses, which, unlike banks, benefit from economies of density. For example, Holmes (2011) studies the expansion of Wal-Mart stores and finds that new stores are always located close to existing stores;

Wal-Mart never jumps to some far-off location, intending to fill the gap between stores later. The main reason for Wal-Mart’s strategy, as suggested by [Holmes \(2011\)](#), is that it gains logistic benefits by operating its stores close to each other. Products sold by Wal-Mart are supplied by regional distribution centers. When stores are opened close to a distribution center, Wal-Mart can save on transport costs and quickly respond to demand shocks. However, in the case of bank branches, such logistical issues are not first-order concerns because both bank deposits and loans are managed through an electronic funds transfer system. The lack of economies of density appears to justify why bank branches are opened in regions remote from existing branches, which ensures that their market areas do not overlap significantly. The spatial diffusion pattern of bank branches is captured by our model through the spatial spillovers of branches on nearby unbanked markets (see Section 3.3). In the model, households can travel to the nearest branch opened in other markets to obtain banking services. Thus, to maximize profits, the central authority tends to open new branches in locations far away from existing ones.

To further elaborate on the geographic patterns of branch expansion between 1987 and 1996, we zoom in on different regions of Thailand defined by the 1996 Socio-Economic Survey (SES) in Thailand, which includes the Bangkok metropolitan, central, north, northeast, and south regions. In the data, the number of branches opened in each region varies significantly over time. For example, of the 32 branches opened in the Bangkok metropolitan region, more than half were opened between 1992 and 1994. The central and north regions did not attract many branches in the early years of our study period, with most branches in these regions opened after 1991. By contrast, many new branch openings occurred in the northeast and south regions in 1991 and 1992.

Figure 6 compares the number of new branches opened each year in the data and the model. Although the model is calibrated only to match the total number of new branches in each year (panel A), the number of new branches opened in each region implied by our model is quite similar to the data (panels B-F). The model captures the waves of branch openings across regions well, including the major upturns and downturns in new branch openings in the data. Specifically, in the Bangkok metropolitan region (panel B), the model captures the initial decline in the number of new branch openings during 1987-1990, but predicts a significant increase in 1991, which is 1 year earlier than the increase in the data. In the central region (panel C), the model captures the trend very well except for the last 2 years of the study period. In the north region (panel D), the model captures the trend well between 1987 and 1991, but it predicts a further increase in the number of new branch openings in 1992 before a decrease in 1993, which is 1 year later than that in the data. Finally, in the northeast and south regions (panels E and F), the model largely captures the ups and downs in the data.

Table 3: Model prediction for the placement of branches.

	(1)	(2)	(3)	(4)	(5)	(6)
	baseline	$\tau_{ij} = \infty$	$\tau_{ij} = \infty$ and $Z_i \equiv \bar{Z}$	randomly choose branch locations 2.5%	median	97.5%
Panel A: Proportion of new branch locations correctly predicted by the model in 1996						
Whole country	86.3%	81.2%	68.5%	38.8%	42.2%	45.7%
Bangkok metropolitan	87.5%	87.5%	53.1%	21.4%	32.4%	43.2%
Central	83.2%	75.6%	59.7%	33.6%	41.2%	48.1%
North	83.0%	73.4%	64.3%	29.7%	36.7%	43.7%
Northeast	89.1%	81.6%	56.6%	33.6%	42.5%	50.4%
South	83.6%	82.4%	74.0%	31.5%	42.5%	52.6%
Panel B: Discrepancy between the predicted and actual years of branch openings across markets						
Whole country	2.38	2.89	4.26	6.76	7.05	7.32
Bangkok metropolitan	1.84	2.03	5.91	5.75	7.06	8.28
Central	2.64	3.40	5.23	6.40	7.04	7.67
North	3.01	3.93	4.18	6.32	7.06	7.77
Northeast	1.42	1.87	3.12	6.41	7.07	7.71
South	2.85	2.73	3.84	6.14	7.00	7.81

Note: Panel A presents the proportion of the locations of branches opened during 1987-1996 that are correctly predicted by different model variants. Panel B presents the discrepancy in the predicted and actual years of branch openings across markets. Column (1) presents the baseline model’s predictions. Column (2) presents the predictions of a model variant that restricts households from traveling to other markets to obtain banking services (i.e., setting $\tau_{ij} = \infty$ for all $i \neq j$). Column (3) presents the predictions of a model variant that further sets productivity across markets to the mean value (i.e, $Z_i \equiv \bar{Z} = 1$ for all $i \in \mathcal{C}$). Columns (4)-(6) present the predictions of a model variant that randomly selects the locations of new branches, with column (5) presenting the median prediction of 1,000,000 independent simulations and columns (4) and (6) indicating the lower and upper bounds of the 95% confidence interval, respectively.

5.2 Predictive Power for the Placement of Branches

We first assess the model’s predictions in 1996, the end of our study period. Panel A of Table 3 presents the proportion of the locations of branches opened during 1987-1996 that are correctly predicted by different model variants. Column (1) presents the baseline model’s predictions. Of the 431 new branches opened from 1987 to 1996 in the whole country, our model correctly predicts the locations of 372 branches, representing a correct prediction ratio of 86.3% ($= 372/431$). Our model provides equally good predictions for the regions within Thailand, as the correct prediction ratios for 1996 uniformly exceed 83% in all five regions.

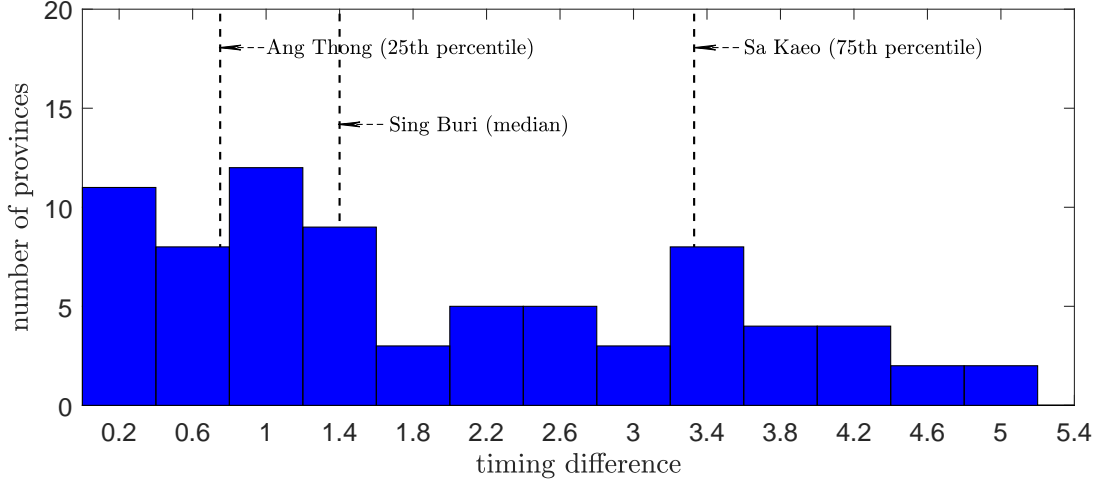
Furthermore, we conduct counterfactual experiments to shed light on the relative importance of each market characteristic in predicting branch locations. We show that the observed branch distribution in the data can be largely interpreted as banks expanding into markets that are populous, productive, and distant from existing branches, yet part of a cluster of markets without

local branches, such that a new branch can serve households from multiple nearby markets. Specifically, markets differ in terms of three aspects in our model: size $\Pi_{i,t}$, productivity Z_i , and distance from the nearest bank branch $d_{i,t}$. In column (2), we present the predictions of a model variant that restricts households from traveling to other markets to obtain banking services (i.e., we set $\tau_{ij} = \infty$ for all $i \neq j$). Thus, the importance of market distance $d_{i,t}$ in explaining new branch locations is quantified by the difference between columns (1) and (2). Column (3) presents the predictions of a model variant that further sets productivity across markets to the mean value (i.e., $Z_i \equiv \bar{Z} = 1$ for all $i \in \mathcal{C}$) and thus the difference between columns (2) and (3) quantifies the importance of heterogeneous market productivity Z_i . Finally, in columns (4)-(6), we consider a model variant that randomly selects the locations of new branches opened between 1987 and 1996. Column (5) presents the median prediction of 1,000,000 independent simulations, and columns (4) and (6) present the lower and upper bounds of the 95% confidence interval, respectively. The difference between columns (3) and (5) quantifies the importance of market size $\Pi_{i,t}$.

As a benchmark without predictive power, columns (4)-(6) show that if the locations of new branches are randomly selected, the median correct prediction ratio for the whole country would be 42.2%, with a tight 95% confidence interval of [38.8%, 45.7%]. Clearly, the selection of branch locations in the data is not random. Comparing columns (3) and (5) in panel A of Table 3, we observe that introducing market size $\Pi_{i,t}$ as the only market-level heterogeneity increases the correct prediction ratio from 42.2% to 68.5% for the whole country. Market size $\Pi_{i,t}$ is especially important for predicting the branch locations in the north and south regions, raising the correct prediction ratio from 36.7% to 64.3% in the north, and from 42.5% to 74.0% in the south.

Comparing columns (2) and (3), the model's correct prediction ratio for the whole country increases from 68.5% to 81.2% if we further add heterogeneous market productivity Z_i . Capturing the differences in Z_i across markets particularly improves the prediction for the Bangkok metropolitan and northeast regions, whose correct prediction ratios are 53.1% and 56.6% in column (3), the lowest of the five regions. Intuitively, the markets around Bangkok are estimated to have higher productivity than markets in other regions (see Figure OA.3 in Online Appendix 1.2). Conversely, compared with Bangkok, markets in the northeast region, although populous, are less productive. Thus, if the model does not feature heterogeneity in market productivity, it will predict too few branches around Bangkok and too many in the northeast (see Table OA.11 in Online Appendix 3.7.5).

Finally, additionally considering the heterogeneity of the distance from the nearest branch $d_{i,t}$ further improves the model's predictive power, as the correct prediction ratio for the whole country increases from 81.2% to 86.3% when we move from column (2) to (1). The heterogeneity of $d_{i,t}$ is especially important in predicting the branch locations in the central, north, and northeast regions of Thailand by allowing branches to serve households from nearby markets without branches.



Note: The province-level timing difference is computed as the average discrepancy between the predicted and actual years of branch openings across markets within each province.

Figure 7: The distribution of province-level timing differences.

The correct prediction ratio reported in panel A of Table 3 shows that the model performs well in predicting new branch locations by the end of our study period, 1996. However, this metric does not reveal whether the model can capture the exact timing for the placement of these branches. Thus, we further evaluate the discrepancies between the predicted and actual timing of branch openings across markets in more depth. Specifically, for each new branch opened between 1987 and 1996 in the data, we compute the difference between its opening year and the model-predicted opening year.⁴² We then compute the average absolute value of this difference for new branch openings during the 1987-1996 period for the whole country and for different regions of Thailand.

Panel B of Table 3 presents the average timing difference across different model variants. Column (1) reports that the average timing difference is 2.38 years across the 431 markets with new branch openings from 1987 to 1996 in Thailand, indicating that the average model-predicted opening time varies from the actual opening time shown by the data by about 2 years. By contrast, columns (4)-(6) show that, if new branch locations are randomly selected, the median value of the average timing difference is 7.05 years, with a tight 95% confidence interval of [6.76, 7.32]. Across regions, our model best predicts the timing of branch openings in the northeast region, with a timing difference from the data of only 1.42 years. The largest timing difference is 3.01 years for the north region, but even this remains significantly lower than the 7.00 years implied by the model variant in which new branch locations are randomly selected.

⁴²We set this difference to 10 years for branches opened between 1987-1996 according to the data but not predicted by the model. Even in 1996, 591 markets did not have branches, as given by the total number of markets less the number of markets with branches in 1986 and the newly established branches ($1,428 - 406 - 431 = 591$).

We also compute the average timing difference at the province level. Figure 7 shows that among the 76 provinces, the median province-level timing difference is 1.4 years, and that 43 provinces have an average timing difference of less than 2 years. Thus, even within provinces, our model has reasonably good prediction accuracy for the dynamics of bank expansion. As two examples, Figures OA.17 and OA.18 in Online Appendix 3.7.6 report branch locations for every year in the 1986-1996 period in the two provinces corresponding to the 25th and 75th percentiles, respectively, of the distribution of province-level average timing differences.

6 A Structural Evaluation of Bank Expansion

In this section, we evaluate the aggregate and distributional impacts of bank expansion through the lens of our model.⁴³ Bank expansion impacts the economy in our model through the provision of loans to entrepreneurs as a result of lower credit entry costs $\psi_{i,t}$ and by giving households access to interest-bearing accounts through lower portfolio adjustment costs $\zeta_{i,t}$. We separately quantify these credit and deposit channels by conducting counterfactual experiments using the model. Specifically, holding the locations of new branches unchanged, we isolate the credit channel by allowing only $\psi_{i,t}$ to decrease with new branch openings, while $\zeta_{i,t}$ remains fixed at its 1986 value. Similarly, to isolate the deposit channel, we allow only $\zeta_{i,t}$ to change, holding $\psi_{i,t}$ fixed at its 1986 value. By decomposing the impact of bank expansion, our model sheds light on the mechanisms behind the observed patterns and phenomena in the data.

6.1 Aggregate Implications of Bank Expansion

We shift the lens of the model from a micro to a macro perspective by aggregating the market-level effects to evaluate the aggregate implications of bank expansion. It is likely that during this period, the aggregate economic variables for Thailand were affected by factors outside the model, i.e., factors other than the expansion of bank branches. Thus, ex ante, we do not expect our model to fully capture the dynamics of the data. Our main purpose is to understand the extent to which patterns at the aggregate level can be explained by our model, in which the main driving force is the exogenous increase in the number of branches over time. The model-implied aggregate implications of bank expansion are likely to be plausible, given that the model correctly predicts

⁴³Although we focus on bank expansion, the model's dynamics are shaped by two forces: bank expansion and migration. In Online Appendix 4.1.2, we separately quantify the role of migration. We show that migration does not play a quantitatively significant role once the model is calibrated to match the low migration rate in the data. Thus, the model dynamics presented in this section mostly reflect the impacts of bank expansion. Moreover, in Online Appendix 4.4, we consider an alternative specification where new branches opened between 1987 and 1996 are exogenously placed at the same locations as those in the data. We show that the quantitative results remain very similar to our main results because our model can correctly predict the majority of branch locations in the data.

the locations of most branches (Table 3) and matches the empirical estimates for the local effects of branch openings (Figure 5).

Panels A-C of Figure 8 show that, in general, the model-implied changes in occupational structure (blue solid lines) are consistent with those in the data (black dashed lines) during this period. The model accounts for about 65% of the occupational shifts among entrepreneurs, workers, and farmers in the data. However, the data indicate that the fraction of entrepreneurs remains roughly unchanged until 1990, when it begins to accelerate, and this pattern is not captured by our model. In the model, the expansion of branch networks generates a steady increase in the fraction of entrepreneurs by allowing them to access bank loans and produce at a larger scale. Then, the resulting increase in demand for local labor boosts wages across markets, generating a strong labor transition from farming to wage labor at the aggregate level.⁴⁴

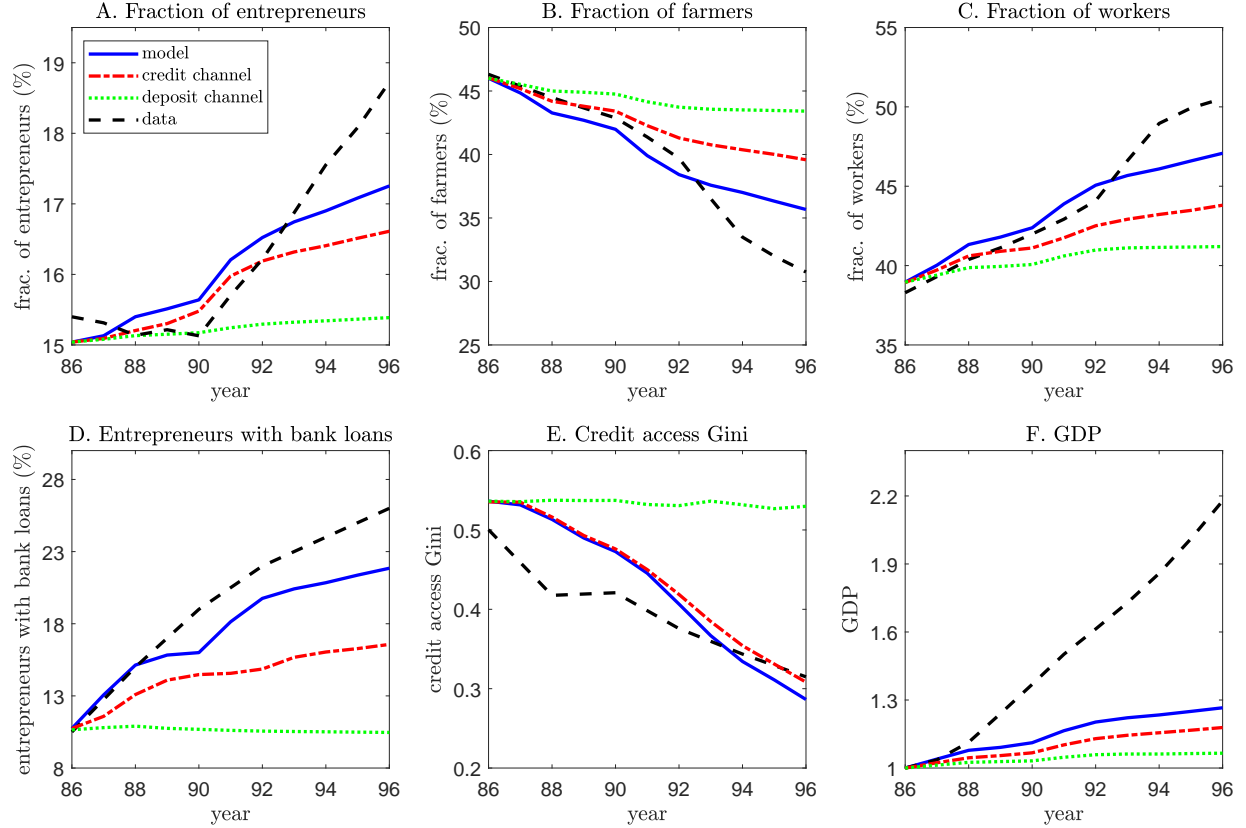
Panels D and E of Figure 8 show that the model accounts well for the significant change in credit access conditions in the data. As shown in panel D, the fraction of entrepreneurs with bank loans increases from 10.5% to 26% between 1986 and 1996 in the data, and the model indicates a similar increase from 10.7% to 21.8%, although it somewhat underpredicts the trend. In panel E, the model implies a downward trend in credit access inequality across markets similar to the trend in the data, but the model-predicted inequality is higher in the early years of the 1986-1996 period compared with the data.

Finally, panel F of Figure 8 shows that the model implies a cumulative GDP growth of 26.5% between 1986 and 1996.⁴⁵ By contrast, according to the data, GDP growth during this period was about 4 times higher than the model's prediction. The large discrepancy in GDP growth but small differences in occupational shifts and entrepreneurs' credit access between the model and the data may be explained by various factors not captured by our model, such as technological growth, human capital development, and surges in international trade and capital flows. These factors could significantly contribute to GDP growth but exert limited effects on other aggregate variables.

The red dash-dotted and green dotted lines in Figure 8 further dissect the impacts of bank expansion through the credit and deposit channels, respectively. Our model implies that the credit channel has a more significant impact than the deposit channel on the promotion of entrepreneurship (panel A) and the labor transition from farmers to workers (panels B and C). Not surprisingly, the credit channel significantly affects the economy's credit access conditions (panels D and E), on which the deposit channel has a minor effect. Intuitively, when the cost of accessing credit is lower, more households become entrepreneurs and borrow from the local

⁴⁴A strong transition from agricultural to non-agricultural occupations is common during the early stages of development in many countries. For example, [Cheremukhin et al. \(2017\)](#) develop a model of structural transformation that explains the dramatic labor force flow across the two sectors in Russia.

⁴⁵Most GDP growth is caused by bank expansion as migration only contributes about 2.7% of such growth (see Online Appendix 4.1.2).



Note: In the model, GDP is calculated according to equation (3.28) in Online Appendix 3.6, in which we also provide a decomposition of GDP growth. The level of GDP in 1986 is normalized to 1. The data variables are constructed in Online Appendix 1.3.

Figure 8: Aggregate dynamics, 1986-1996.

branch to expand the scale of their businesses, which boosts employment and output.

In panel F, the credit channel alone generates a GDP growth of 17.8% during this period, compared with a GDP growth of 6.5% from the deposit channel. Interestingly, complementarity exists between the two channels. When both channels are active, GDP growth is 26.5%, which is greater than the sum of each channel's separate effect (i.e., $17.8\% + 6.5\% = 24.3\%$).⁴⁶ First, complementarity operates within markets with branches. The deposit channel allows households to accumulate wealth faster through interest-bearing deposit accounts. The increase in the level of wealth relaxes the collateral constraints, allowing talented but wealth-constrained entrepreneurs

⁴⁶The complementarity also exists for other variables, not only for GDP growth. In general, the quantitative impacts of this complementarity vary across variables. For example, there is a strong complementarity between the channels in terms of boosting the fraction of entrepreneurs with loans (panel D), as this fraction decreases if the deposit channel works alone because some households accumulate sufficient wealth in interest-bearing accounts and become self-financed entrepreneurs. However, the fraction of entrepreneurs with loans increases from 16.6% to 21.8% when the deposit channel is combined with the credit channel.

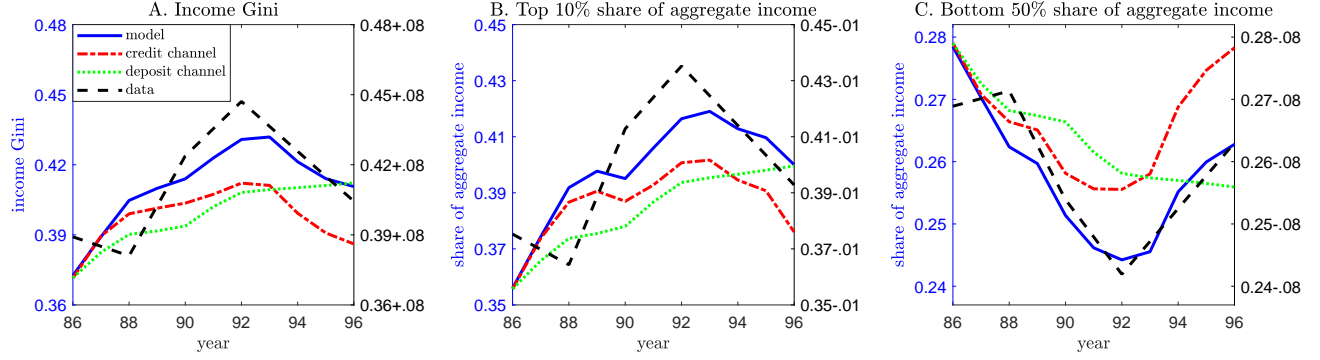
to obtain more bank loans, which amplifies the credit channel. Second, complementarity operates across markets, improving the allocative efficiency of the additional funds provided through the deposit channel. The cross-market complementarity between the deposit and credit channels is, crucially, attributable to the flow of funds among bank branches located in different spatial markets. Specifically, when branches expand and the cost of accessing deposit accounts falls, households increase their holdings of deposits, which makes additional funds available to entrepreneurs through the country’s capital market. In the absence of the credit channel, the credit entry costs $\psi_{i,t}$ remain high in markets with new branch openings between 1987 and 1996; thus, talented entrepreneurs in these markets still lack access to credit. As a result, the additional funds provided through the deposit channel flow to markets that already have branches in 1986; the funds are absorbed by the less talented entrepreneurs in these markets and hence have a limited impact on aggregate output. By contrast, in the presence of the credit channel, the credit entry costs $\psi_{i,t}$ decline in markets in which new branches open, allowing talented entrepreneurs in these markets to borrow and expand their businesses. As a result, the additional funds provided through the deposit channel flow to markets with new branch openings; the funds are borrowed by more talented entrepreneurs and hence have a greater impact on aggregate output. See Online Appendix 4.2.1 for clarification of the above channels using the model.

6.2 Dynamics of Income Inequality

Now, we examine the implications of bank expansion on the dynamics of income inequality to elucidate the underlying channels. We focus on the changes in income inequality over time rather than the levels per se. Note that none of the inequality moments are used in our calibration, and thus this section provides both a model validation and an explanation through the lens of the model.

Overall Change in Income Inequality Across Households. Figure 9 illustrates the implications for income inequality across all households in the economy. In the data, panel A shows that the income Gini coefficient increases from 1986 to 1992 and decreases thereafter (black dashed line, right y-axis). This salient inverted U-shape is consistent with the Kuznets’ hypothesis. The Gini coefficient does not capture the entire distribution of income, especially the higher-order moments and tail distributions (Guvenen et al., 2015, 2017). In panels B and C, we illustrate the dynamics of different income groups, plotting the share of aggregate income earned by the top 10% and bottom 50% of households in the income distribution. In the data, the share of the top 10% displays an inverted U-shape, similar to the Gini coefficient in panel A. By contrast, the share of the bottom 50% is U-shaped.

The blue solid lines in Figure 9 plot the income inequality dynamics predicted by our model,



Note: Panel A plots the income Gini coefficient across all households in the economy. We construct the income distribution of all households and compute aggregate income as the sum of all households' income. Panels B and C plot the share of aggregate income earned by the top 10% and bottom 50% of the distribution, respectively. The left y-axis is for the model (i.e., model, credit channel, and deposit channel) and the right y-axis is for the data. The right and left y-axes differ by a constant, which represents the average level differences between the model (blue solid line) and data (black dashed line) for the 1986-1996 period. The data variables are constructed in Online Appendix 1.3.

Figure 9: Overall income inequality across households, 1986-1996.

based on the left y-axis. Comparing the blue solid and black dashed lines, it is evident that by focusing on bank expansion as the main driving force, the model captures the hump-shaped dynamics of income inequality well. In both the model and data, the income Gini increases significantly from 1986 to 1992 and declines thereafter.

The model sheds further light on the impact on the income Gini through the credit and deposit channels of bank expansion. In panel A, the credit channel (red dash-dotted line) alone can generate hump-shaped dynamics, although the peak-trough difference is smaller than that in the baseline model. By contrast, purely through the deposit channel (green dotted line), the income Gini increases persistently over the 1986-1996 period. When both channels are active, the baseline model (blue solid line) implies a very pronounced inverted U-shape for the income Gini, as in the data.

The right and left y-axes in each panel of Figure 9 differ by a constant, which represents the difference between the model and the data for the average level of the variable of interest for the 1986-1996 period. It is evident that the average share of the top 10% (panel B) in the model is very similar to that in the data, differing by only 1%. However, the average level of the income Gini (panel A) is about 0.08 lower and the average share of the bottom 50% (panel C) is about 8% higher in the model than in the data. The reason that our model underpredicts the level of the income Gini and overpredicts the bottom 50% income concentration is that it does not incorporate income heterogeneity for workers/farmers within the same market (Cagetti and Nardi, 2006; Jeong and Townsend, 2007). Although we could potentially fix this issue by introducing within-market income heterogeneity for workers, it would greatly increase the complexity of the

model. Given that the main focus of our paper is on the spatial implications of bank expansion, we leave this extension for future research.

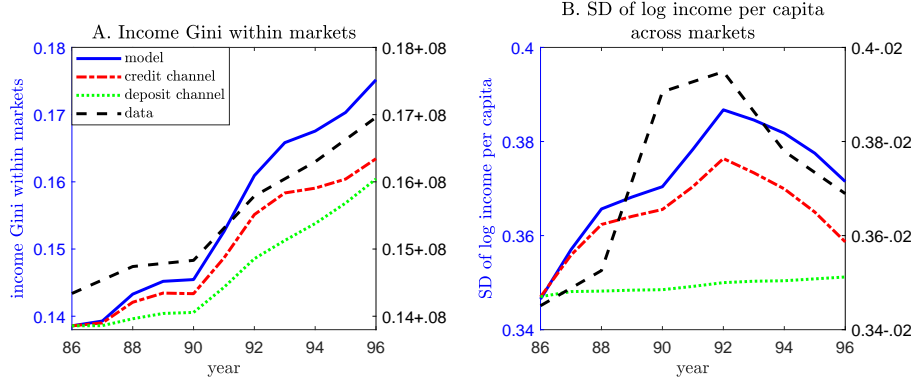
Income Inequality Within and Across Markets. The overall income inequality can be decomposed into inequality across households within the same markets and inequality across markets. Panel A of Figure 10 plots the within-market income Gini coefficient, computed using the income distribution of households within the same markets. In both the data and model, the within-market income Gini increases steadily between 1986 and 1996. Similar to panel A of Figure 9, due to the lack of worker/farmer heterogeneity, the average level of the within-market income Gini predicted by the model is about 0.08 lower than that in the data.

The red dash-dotted and green dotted lines illustrate the impacts of the credit and deposit channels on within-market income inequality. Both channels significantly increase income inequality but for different reasons. Intuitively, the credit channel allows talented but wealth-constrained local entrepreneurs to borrow, increasing their business income. Despite wages increasing as well, the within-market income gap between talented entrepreneurs and workers expands, resulting in higher income inequality after the expansion of bank branches. By contrast, the deposit channel allows talented but wealth-constrained local households to accumulate more wealth through interest-bearing deposit accounts, eventually enabling them to start and expand their own businesses. Simultaneously, the deposit channel allows already wealthy households to expand their deposits, increasing their financial income. As these wealthy and talented households already have higher incomes than other households, this increases within-market income inequality.

Panel B of Figure 10 illustrates income inequality dynamics across markets. We plot the standard deviation of log market-level income per capita. In the data, cross-market income inequality increases during the 1986-1992 period and declines thereafter (black dashed line, right y-axis), exhibiting a similar inverted U-shape to that of the overall income Gini in panel A of Figure 9.⁴⁷

By reproducing the inverted U-shape for cross-market income inequality (blue solid lines, left y-axes in panel B of Figure 10), our model offers one simple mechanism to rationalize it. The expansion of branches promotes financial inclusion across markets. The fraction of markets with local branches increases from a low initial level of 28.4% ($= 406/1,428$) in 1986 to a high level of 58.6% ($= (406 + 431)/1,428$) in 1996. Thus, in the early years of our study period when the majority of markets do not have branches, opening branches leads to higher cross-market income inequality. Conversely, in later years, as the majority of markets already have branches, opening more branches lowers cross-market income inequality. Moreover, new branch openings must have a large impact on local income to generate the inverted U-shape in cross-market income inequality.

⁴⁷This pattern is also found at the village level. Townsend (2011, Chapter 3.2) documents that income inequality across villages increases until about 1992, when it begins to decrease.

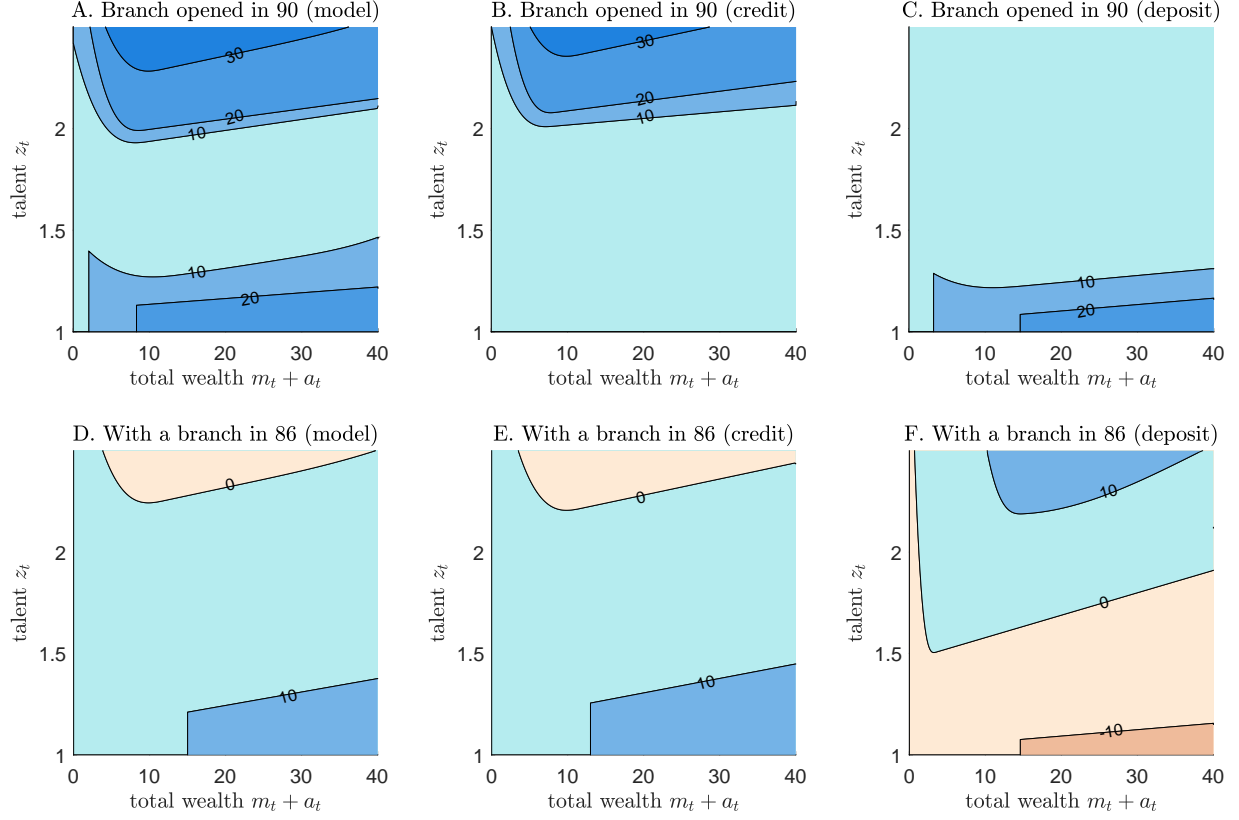


Note: For each market, we construct the income distribution of households and calculate the income Gini coefficient across these households. Panel A plots the average within-market income Gini coefficient across all markets in the economy. Panel B plots the standard deviation (SD) of log market-level income per capita across markets, where market-level income is obtained by aggregating the income of households within each market. We normalize market-level income per capita by its average value across all the markets. The left y-axis is for the model (i.e., model, credit channel, and deposit channel) and the right y-axis is for the data. The right and left y-axes differ by a constant, which represents the average level differences between the model (blue solid line) and data (black dashed line) for the 1986-1996 period. The data variables are constructed in Online Appendix 1.3.

Figure 10: Income inequality within and across markets, 1986-1996.

This becomes evident if we decompose the impacts into the credit and deposit channels: the credit channel significantly boosts local income (see panel F of Figure 8), generating a similar inverted U-shape (red dash-dotted line), but the mild effect of the deposit channel is insufficient to generate this shape. Instead, as the green dotted line in panel B of Figure 10 shows, the deposit channel leads to a slight increase in cross-market income inequality between 1986 and 1996 due to the general equilibrium effect. As new branches are opened, households' demand for deposits increases through the deposit channel, resulting in a reduction in the equilibrium interest rate for the whole economy. The lower interest rate effectively reduces the costs of borrowing for entrepreneurs with credit access, and thus the income of markets that already have branches in 1986 increases further. Because these markets initially have higher income than others, cross-market income inequality increases.

The level of cross-market income inequality predicted by the model is largely consistent with that in the data, with the average level differing only by 0.02 (comparing the left and right y-axes in panel B of Figure 10). This suggests that the model captures the main regional heterogeneity in the data, providing a further out-of-sample validation for the spatial heterogeneity highlighted in the model. In Figure OA.37 in Online Appendix 4.3.1, we show that the model can still generate an inverted U-shape for cross-market income Gini dynamics if we exclude market-level productivity heterogeneity, but the Gini level is lower.



Note: The consumption-equivalent welfare gains for the 1986-1996 period for households of different total wealth $m_t + a_t$ and talent z_t are calculated (see Online Appendix 3.4). Panels A-C focus on a market where no branch exists in 1986 and a branch is opened in 1990. The three panels present the implications of the baseline model, credit channel, and deposit channel, respectively. Panels D-F focus on a market that has a branch in 1986. Both markets have the same median level of productivity (0.99). Each contour line represents households with the same welfare change, and the percentage change in welfare is indicated by the number on each line.

Figure 11: Welfare changes across households within the same markets, 1986-1996.

6.3 Welfare Implications Within and Across Markets

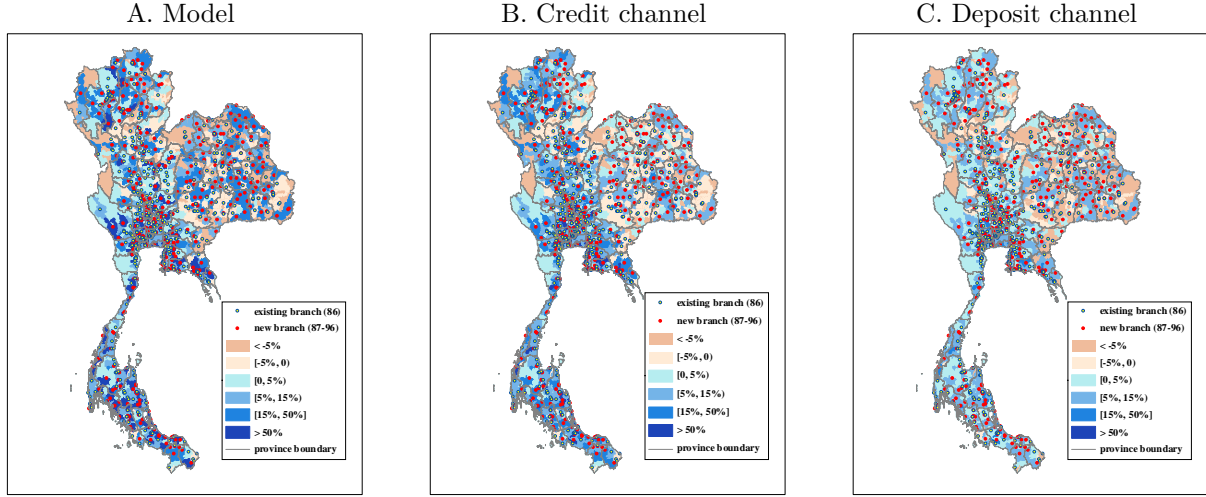
Our model provides well-defined normative metrics to evaluate the welfare implications of bank expansion. For the 1986-1996 period, the overall country-wide (consumption-equivalent) welfare gains predicted by the model are 19.9%; 11.4% of this is attributed to the credit channel and 4.5% to the deposit channel, with the remainder (4.0%) due to the complementarity of these channels (see Section 6.1). Both channels have significant redistributive effects within and across markets as discussed below.

Welfare Within Markets. We first investigate welfare changes across households with different levels of total wealth $m_t + a_t$ and talent z_t . Panels A-C of Figure 11 focus on a market in which the branch opens in 1990 (i.e., no branch exists in 1986), with the three panels representing the

implications of the baseline model, credit channel, and deposit channel, respectively. It is evident that panel A displays a pattern similar to those of panels B and C combined, although the exact magnitudes of welfare gains differ slightly due to the interaction between the credit and deposit channels, which affects the equilibrium interest rate and wages. As shown in panel B, households in the upper region experience large welfare gains due to the credit channel. These households are talented but wealth-constrained entrepreneurs. After a branch is opened, they benefit from the low credit entry costs $\psi_{i,t}$ and borrow from the branch to expand their businesses, leading to a significant increase in their income and consumption. Panel C shows that the wealthy but not talented households in the lower-right region also experience significant welfare gains due to the deposit channel. After a branch is opened, these households benefit from the low portfolio adjustment costs $\zeta_{i,t}$ and save a large fraction of their wealth in bank deposits in the pursuit of high interest income. Households in the middle region (i.e., the region enclosed by “10” in panel A) have the smallest welfare gains (less than 10%) among all households. These households are mostly mediocre entrepreneurs, running small and medium-sized businesses that are financed largely by their own wealth. Thus, they do not benefit greatly from the lower $\psi_{i,t}$ and $\zeta_{i,t}$ after a branch is opened. The relatively large welfare gains of talented and wealthy households are consistent with the increase in within-market income inequality between 1986 and 1996 (panel A of Figure 10) because these households already have higher income than other households.

Panels D-F of Figure 11 focus on a market that already has a branch in 1986. Panel D shows that households in this market have much smaller and even negative welfare gains compared with those in panel A, purely as a result of the general equilibrium effect. Specifically, the expansion of bank branches increases the economy-wide demand for loans more than it increases the demand for deposits, leading to a rise in the equilibrium interest rate. Households in the lower-right region enclosed by “10” have larger welfare gains than other households in the market because they are wealthier; they hold more deposits and thus benefit more from the higher interest rate. However, households in the upper region enclosed by “0” experience welfare losses; these are talented but wealth-constrained entrepreneurs, who borrow large amounts of loans to finance their businesses. The higher interest rate increases their costs of production and reduces their business income.

Panel E of Figure 11 illustrates the impact of the credit channel on the market that already has a branch in 1986. In this counterfactual experiment, new branch openings in other markets no longer reduce portfolio adjustment costs. The general equilibrium effect is even stronger, resulting in a greater increase in the equilibrium interest rate compared with panel D. Thus, both the upper region enclosed by “0” and the lower-right region enclosed by “10” expand in panel E. Panel F focuses on the impact of the deposit channel. In this counterfactual experiment, new branch openings in other markets only reduce portfolio adjustment costs but not credit entry costs. The demand for deposits increases, resulting in a lower equilibrium interest rate—the



Note: Market-level welfare gains are household-level welfare gains weighted by the distribution of households. Panels A-C represent the baseline model, credit channel, and deposit channel, respectively.

Figure 12: Market-level welfare changes, 1986-1996.

general equilibrium effect flips the sign of the effect. Thus, the pattern displayed in panel F is the opposite to that in panel E: households in the upper region experience welfare gains, whereas those in the lower region experience welfare losses.

Welfare Across Markets. We calculate changes in market-level welfare between 1986 and 1996, defined as changes in household-level welfare weighted by the distribution of households. Because of migration, market-level welfare changes reflect not only changes in the standard of living for households but also a selection effect due to the change in the composition of households. The selection effect does not measure whether non-migrants are better or worse off. To provide a market-level welfare measure without selection effects, we present the welfare implications in a similarly calibrated model without migration in Figure OA.27 in Online Appendix 4.1.

Panel A of Figure 12 focuses on the predictions of the baseline model. Different markets exhibit highly heterogeneous welfare changes. Markets that are initially far away from branches but receive new branches during the 1987-1996 period (red dots) experience large welfare gains, ranging from 10% to 90%. Among these markets, the most productive markets that receive new branch openings in the early years of the period have the largest welfare gains. Markets that already have branches in 1986 (yellow dots) experience small welfare changes of about -5% to 11% , which can be decomposed into a general equilibrium effect and a selection effect. The general equilibrium effect is caused by the higher interest rate after branch expansion, which benefits depositors but hurts entrepreneurs borrowing bank loans, resulting in a net welfare gain of about 2% . The selection effect is caused by migration, as talented entrepreneurs tend to leave

less productive markets and move to more productive ones. The selection effect on market-level welfare is negative for the former but positive for the latter. Finally, the markets that do not have branches throughout the entire 1986-1996 period experience small welfare changes of about -7% to 14% . The negative selection effect from migration in these markets is strong because some talented entrepreneurs based in these markets migrate to markets with branches.

Panels B and C of Figure 12 present the welfare changes that occur through the credit and deposit channels, respectively. The overall patterns are similar to panel A, although the variation across markets is less dramatic because new branch openings have less impact through each channel alone than through the combined channels.

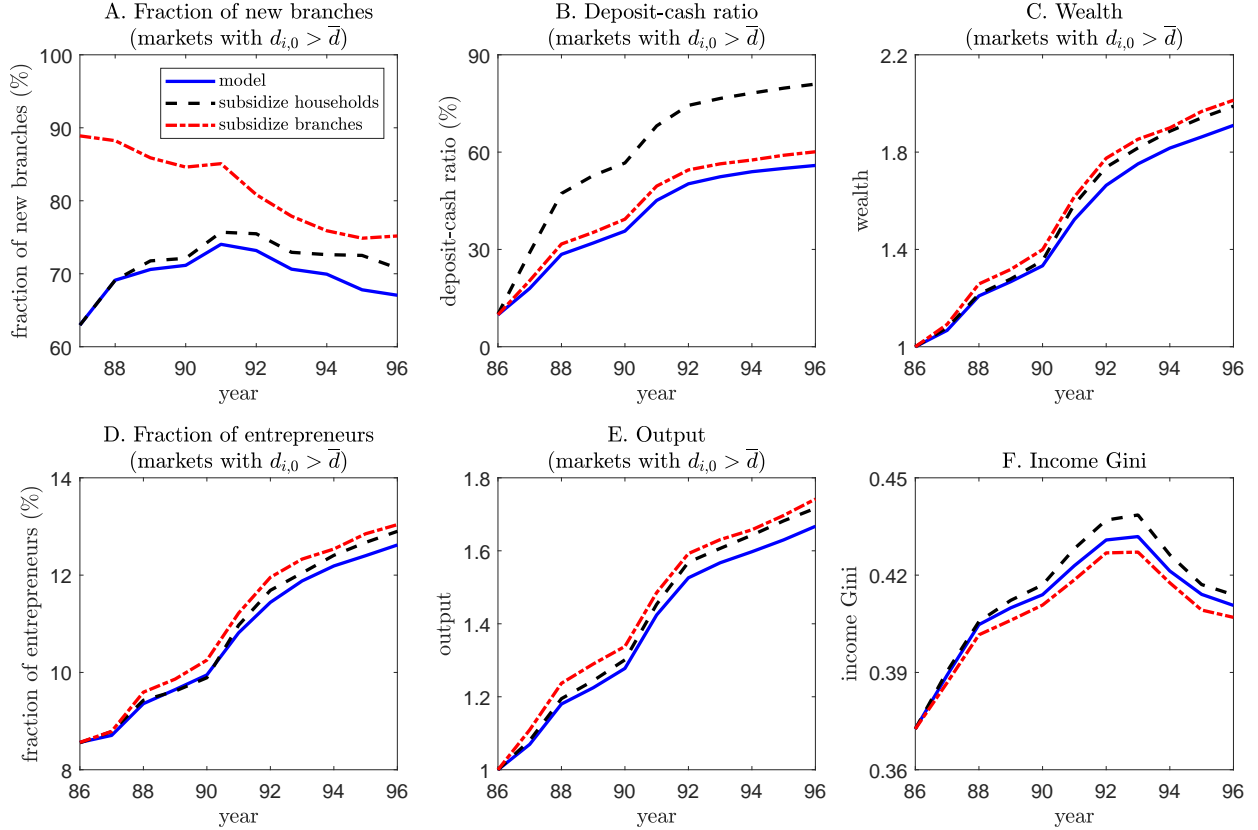
7 Policy Counterfactual

Many developing countries directly target underbanked regions through government policies to foster financial inclusion. As a final exercise, we use the model to evaluate two such policies, illustrating their potential impacts through a change in the distribution of branches.

The first policy we examine is motivated by the need for rural deposit mobilization. The rural sector is the primary source of savings in many low-income countries and emerging market economies, such as Bangladesh, Indonesia, the Philippines, and Thailand. However, the ability to mobilize rural funds is quite limited, with one of the major reasons being that rural people prefer to hold cash and non-financial assets over bank deposits. We consider a policy to mobilize rural deposits by subsidizing the portfolio adjustment costs $\zeta_{i,t}$ for households living in markets distant from bank branches. Specifically, when households located in markets where $d_{i,0} > \bar{d}$ make a deposit or withdrawal at a branch, they incur an effective pecuniary cost of $\zeta_{i,t} - s_1$, instead of $\zeta_{i,t}$, with the amount s_1 capturing the cash subsidy transferred from the government to households.⁴⁸ The variable $d_{i,0}$ is the market's distance from the nearest branch in 1986 and \bar{d} is the median distance from the nearest branch across all markets without branches in 1986.

Although households in rural areas may respond to the subsidized portfolio adjustment costs by increasing their deposits, there is little scope for deposit mobilization if households have limited access to financial institutions. Therefore, we consider a second policy that directly subsidizes the establishment of branches rather than subsidizing households. Specifically, we modify equation (3.17) by subsidizing the profits $\Theta_{i,t}$ of new branches opened between 1987 and 1996 in markets with $d_{i,0} > \bar{d}$ at a rate of s_2 . This policy is motivated by policymakers' desire for commercial lenders, credit unions, and government-owned banks to expand into rural areas. For example, Bangladesh implemented such policies during the second half of the 1970s in an effort to stimulate

⁴⁸This policy can be implemented because the government only needs to know the markets' distances from the nearest branch and which households live in these markets.



Note: The black dashed line represents the policy that subsidizes the portfolio adjustment costs of households in markets for which distance from the nearest branch in 1986, $d_{i,0}$, is greater than \bar{d} , the median distance from the nearest branch across all markets without branches in 1986. The red dash-dotted line represents the policy that subsidizes new branches opened in markets with $d_{i,0} > \bar{d}$. Panel A plots the fraction of new branches opened since 1987 in markets where $d_{i,0} > \bar{d}$. Panels B-E plot the deposit-cash ratio, wealth (cash + deposits), fraction of entrepreneurs, and output, respectively, of markets with $d_{i,0} > \bar{d}$. Panel F plots the overall income Gini.

Figure 13: Impacts of financial sector policies.

the expansion of rural banking services. Commercial banks wishing to open urban branches were required by the Bangladesh Bank to establish two rural branches as a condition of their license to open an urban branch. The establishment of branches in rural areas directly reduced the deposit costs in nearby regions, channeling rural funds to urban areas.

To make the two policies comparable, we calibrate $s_1 = 0.03$ and $s_2 = 25\%$ so that total costs are the same for both policies and amount to 0.15% of GDP for the 1987-1996 period. These costs are financed by lump-sum taxes levied on households.⁴⁹ Figure 13 evaluates the impacts of the two policies against our baseline model without policy subsidies. Panel A plots

⁴⁹Because the costs are not particularly high, the policy implications are virtually unchanged if the costs are not paid by households. For both policies, the government provides subsidies for markets where $d_{i,0} > \bar{d}$, which is based on the distance $d_{i,0}$ in the initial year, 1986, rather than the distance $d_{i,t}$ in each year t because practically the government would not be tracking the evolution of distances from branches over time.

the fraction of new branches that open in distant markets (i.e., $d_{i,0} > \bar{d}$). Relative to the baseline model (blue solid line), both policies result in more branch openings in distant markets, which helps reach the unbanked population. However, the timing and magnitude of the two policies' impacts are quite different. Directly subsidizing branches leads to an immediate and dramatic increase in the number of new branch openings in distant markets in 1987 (red dash-dotted line). However, subsidizing household portfolio adjustment costs has little effect early on, and the effect becomes pronounced only in later years (black dashed line). Intuitively, the portfolio adjustment cost subsidy provides incentives for households to hold more deposits, allowing them to accumulate wealth faster. Wealth accumulation increases households' demand for collateralized loans, motivating more branches to open in these markets. However, because it takes time to adjust portfolios and accumulate wealth, the subsidy is not effective during the early years of implementation.

Panels B and C support the above mechanism by illustrating the policies' impacts on the aggregate deposit-cash ratio and wealth of distant markets, respectively. Subsidizing branches generates only a moderate increase in the deposit-cash ratio due to the increased number of new branch openings in distant markets, which effectively reduces portfolio adjustment costs. By contrast, subsidizing households results in a significant increase in the deposit-cash ratio. The latter policy has a strong effect because the subsidy itself directly lowers households' portfolio adjustment costs in distant markets, in addition to attracting new branch openings. Although subsidizing households strongly boosts the deposit-cash ratio, panel C shows that subsidizing branches has a greater effect on wealth accumulation because it results in more new branch openings in distant markets (see panel A) than the policy subsidizing households. This suggests that subsidizing branches is more effective in mobilizing rural funds, highlighting the importance of promoting financial inclusion through increased access to financial institutions.⁵⁰

Panels D and E show that both policies increase the fraction of entrepreneurs and output growth in distant markets, respectively. Again, the policy subsidizing branches is more effective than that subsidizing households. For example, for the study period, 1986-1996, output growth in the distant markets is 66.7% under the baseline model without policy subsidies; if households are subsidized, output growth increases to 71.6%, whereas if branches are subsidized, it increases to 74.2%. Nevertheless, in our model, because the total number of new branch openings is given exogenously, the opening of more branches in distant markets implies fewer branch openings in other markets.⁵¹ As such, the output growth of markets close to existing branches in 1986 is

⁵⁰According to the 2017 World Bank Global Findex survey, more than 30% of adults in Brazil, Indonesia, Kenya, and the Philippines cite distance (financial institutions are too far away) as their reason for being unbanked (Demirguc-Kunt et al., 2018).

⁵¹In reality, both policies would influence the total number of new branch openings. Our model does not address this issue because the total number of new branch openings is exogenously given by the data. To provide some suggestive results, we calculate the profits for each new branch opening according to equation (3.17). The average

lower under the two policies than it is in the baseline model.

Finally, panel F shows that compared with the baseline model, subsidizing branches results in lower overall income inequality across households. By attracting new branch openings, this policy boosts the income of distant markets, most of which have lower income than other markets due to financial exclusion. As a result, cross-market income inequality falls, resulting in a lower overall income Gini compared with the baseline model. By contrast, subsidizing households leads to higher overall income inequality than the baseline model. As discussed for panel A of Figure 10, the deposit channel increases income inequality within markets as talented and wealthy households benefit more from reduced portfolio adjustment costs. Under this policy, even though cross-market inequality decreases due to a few more branch openings in distant markets, the increase in within-market inequality dominates this effect, resulting in a higher overall income Gini than the baseline model.

8 Conclusion

The interaction between spatial heterogeneity and financial deepening is central to a wide range of important phenomena in the process of economic development. This paper develops a spatial equilibrium model with heterogeneous households to study economic transitions accompanied by dynamic bank expansion, a departure from typical calibration exercises based on models without geography. To make the model computable, we propose an algorithm that solves the combinatorial problem of bank expansion numerically.

We apply the model to Thai data for the 1986-1996 period, calibrate it, and make predictions. By integrating theory with measurement and data, our paper advances the understanding of bank branch expansion in two main aspects. First, by modeling endogenous locations of branch expansion, our model reveals that market size, productivity, and access to finance are three important market characteristics that explain the geographic distribution of branches in the data, helping us understand the main endogeneity issues of branch locations.

Second, our paper is the first attempt to evaluate the impacts of bank expansion through the lens of a spatial equilibrium model disciplined by micro evidence. We use a DID approach on pairs of treatment and control markets, with matched covariates that capture market size, productivity, and access to finance, as guided by the model, to estimate the local impacts of branch openings. These estimates at the level of local markets are used to calibrate and validate the model, which is then further applied to quantitatively explore the rich aggregate and distributional implications

profits across the 431 new branches opened during the 1987-1996 period are 91.3, 97.5, and 107.7 for the baseline model, household subsidy policy, and branch subsidy policy, respectively. This suggests that both policies can potentially increase the total number of new branch openings relative to the baseline model, with the latter policy having a possibly greater impact than the former.

of bank expansion, as well as the implications of alternative financial sector policies.

Our model should be viewed as a step toward improving understanding of bank expansion and financial deepening across regions. For tractability, we must omit certain factors. We do not address potential spillovers, the role of technological diffusion, strategic competition among banks, or within-market wage heterogeneity. The framework that we propose in this paper can be extended in future research to clarify the roles of these forces in spatial development.

References

- Abadie, Alberto, Alexis Diamond, and Jens Hainmueller. 2010. "Synthetic Control Methods for Comparative Case Studies: Estimating the Effect of California's Tobacco Control Program." *Journal of the American Statistical Association*, 105(490): 493–505.
- Abadie, Alberto, and Javier Gardeazabal. 2003. "The Economic Costs of Conflict: A Case Study of the Basque Country." *American Economic Review*, 93(1): 113–132.
- Abiad, Abdul, Nienke Oomes, and Kenichi Ueda. 2008. "The quality effect: Does financial liberalization improve the allocation of capital?" *Journal of Development Economics*, 87(2): 270–282.
- Acemoglu, Daron, and Melissa Dell. 2010. "Productivity Differences between and within Countries." *American Economic Journal: Macroeconomics*, 2(1): 169–188.
- Agarwal, Sumit, Abhiroop Mukherjee, and S. Lakshmi Naaraayanan. 2022. "Roads and Loans." *Review of Financial Studies*, forthcoming.
- Aguirregabiria, Victor, Robert Clark, and Hui Wang. 2016. "Diversification of geographic risk in retail bank networks: evidence from bank expansion after the Riegle-Neal Act." *RAND Journal of Economics*, 47(3): 529–572.
- Aguirregabiria, Victor, Robert Clark, and Hui Wang. 2020. "The Geographic Flow of Bank Funding and Access to Credit: Branch Networks, Local Synergies, and Competition." University of Toronto, Department of Economics Working Papers tecipa-639.
- Ahn, SeHyoung, Greg Kaplan, Benjamin Moll, Thomas Winberry, and Christian Wolf. 2018. "When Inequality Matters for Macro and Macro Matters for Inequality." *NBER Macroeconomics Annual*, 32(1): 1–75.
- Alvarez, Fernando, and Francesco Lippi. 2009. "Financial Innovation and the Transactions Demand for Cash." *Econometrica*, 77(2): 363–402.
- Alvarez, Fernando, Andrew Atkeson, and Chris Edmond. 2009. "Sluggish Responses of Prices and Inflation to Monetary Shocks in an Inventory Model of Money Demand." *The Quarterly Journal of Economics*, 124(3): 911–967.
- Alves, Felipe, Greg Kaplan, Benjamin Moll, and Giovanni L. Violante. 2020. "A Further Look at the Propagation of Monetary Policy Shocks in HANK." *Journal of Money, Credit and Banking*, 52(S2): 521–559.
- Amaral, Pedro S., and Erwan Quintin. 2010. "Limited Enforcement, Financial Intermediation, And Economic Development: A Quantitative Assessment." *International Economic Review*, 51(3): 785–811.
- Assuncao, Juliano, Sergey Mityakov, and Robert M. Townsend. 2020. "Public ownership and anti-preemption." Working Papers.
- Auclert, Adrien. 2019. "Monetary Policy and the Redistribution Channel." *American Economic Review*, 109(6): 2333–2367.
- Auclert, Adrien, Matthew Rognlie, and Ludwig Straub. 2020. "Micro Jumps, Macro Humps: Monetary Policy and Business Cycles in an Estimated HANK Model." National Bureau of Economic Research, Inc NBER Working Papers 26647.
- Augsburg, Britta, Ralph De Haas, Heike Harmgart, and Costas Meghir. 2015. "The Impacts of Microcredit: Evidence from Bosnia and Herzegovina." *American Economic Journal: Applied Economics*, 7(1): 183–203.
- Bailey, Martha J., and Andrew Goodman-Bacon. 2015. "The War on Poverty's Experiment in Public Medicine: Community Health Centers and the Mortality of Older Americans." *American Economic Review*, 105(3): 1067–1104.
- Bandiera, Oriana, Gerard Caprio, Patrick Honohan, and Fabio Schiantarelli. 2000. "Does Financial Reform Raise or Reduce Saving?" *The Review of Economics and Statistics*, 82(2): 239–263.
- Banerjee, Abhijit, Esther Duflo, Rachel Glennerster, and Cynthia Kinnan. 2015. "The Miracle of Microfinance? Evidence from a Randomized Evaluation." *American Economic Journal: Applied Economics*, 7(1): 22–53.
- Banerjee, Abhijit V, and Andrew F Newman. 1993. "Occupational Choice and the Process of Development." *Journal of Political Economy*, 101(2): 274–98.
- Banerjee, Abhijit V., and Esther Duflo. 2014. "Do Firms Want to Borrow More? Testing Credit Constraints Using a Directed Lending Program." *Review of Economic Studies*, 81(2): 572–607.

- Barboni, Giorgia, Erica Field, and Rohini Pande.** 2022. "Rural Banks Can Reduce Poverty: Evidence from 870 Indian Villages." Working Papers.
- Baumol, William J.** 1952. "The Transactions Demand for Cash: An Inventory Theoretic Approach." *Quarterly Journal of Economics*, 66: 545–556.
- Bayer, Christian, Ralph Luetticke, Lien Pham-Dao, and Volker Tjaden.** 2019. "Precautionary Savings, Illiquid Assets, and the Aggregate Consequences of Shocks to Household Income Risk." *Econometrica*, 87(1): 255–290.
- Beng, Daniel Lian Choon.** 1994. "Gradual Financial Reform in Action: The Case of Thailand, 1979–92." *ASEAN Economic Bulletin*, 10(3): 297–315.
- Bergquist, Lauren Falcao, Benjamin Faber, Thibault Fally, Matthias Hoelzlein, Edward Miguel, and Andres Rodriguez-Clare.** 2020. "Scaling Agricultural Policy Interventions: Theory and Evidence from Uganda." Working Paper.
- Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan.** 2004. "How Much Should We Trust Differences-In-Differences Estimates?" *The Quarterly Journal of Economics*, 119(1): 249–275.
- Black, Sandra E., and Philip E. Strahan.** 2002. "Entrepreneurship and Bank Credit Availability." *Journal of Finance*, 57(6): 2807–2833.
- Boar, Corina, Denis Gorea, and Virgiliu Midrigan.** 2022. "Why Are Returns to Private Business Wealth So Dispersed?" National Bureau of Economic Research, Inc NBER Working Papers 29705.
- Bryan, Gharad, and Melanie Morten.** 2019. "The Aggregate Productivity Effects of Internal Migration: Evidence from Indonesia." *Journal of Political Economy*, 127(5): 2229 – 2268.
- Buera, Francisco J., and Yongseok Shin.** 2011. "Self-insurance vs. self-financing: A welfare analysis of the persistence of shocks." *Journal of Economic Theory*, 146(3): 845–862.
- Buera, Francisco J., and Yongseok Shin.** 2013. "Financial Frictions and the Persistence of History: A Quantitative Exploration." *Journal of Political Economy*, 121(2): 221 – 272.
- Buera, Francisco J., Joseph P. Kaboski, and Yongseok Shin.** 2011. "Finance and Development: A Tale of Two Sectors." *American Economic Review*, 101(5): 1964–2002.
- Burgess, Robin, and Rohini Pande.** 2005. "Do Rural Banks Matter? Evidence from the Indian Social Banking Experiment." *American Economic Review*, 95(3): 780–795.
- Cagetti, Marco, and Mariacristina De Nardi.** 2006. "Entrepreneurship, Frictions, and Wealth." *Journal of Political Economy*, 114(5): 835–870.
- Caliendo, Lorenzo, Maximiliano Dvorkin, and Fernando Parro.** 2019. "Trade and Labor Market Dynamics: General Equilibrium Analysis of the China Trade Shock." *Econometrica*, 87(3): 741–835.
- Caskey, John P.** 1994. *Fringe Banking: Check-Cashing Outlets, Pawnshops, and the Poor*. New York: Russell Sage Foundation.
- Cetorelli, Nicola, and Philip E. Strahan.** 2006. "Finance as a Barrier to Entry: Bank Competition and Industry Structure in Local U.S. Markets." *Journal of Finance*, 61(1): 437–461.
- Cheremukhin, Anton, Mikhail Golosov, Sergei Guriev, and Aleh Tsyvinski.** 2015. "The Economy of People's Republic of China from 1953." National Bureau of Economic Research, Inc NBER Working Papers 21397.
- Cheremukhin, Anton, Mikhail Golosov, Sergei Guriev, and Aleh Tsyvinski.** 2017. "The Industrialization and Economic Development of Russia through the Lens of a Neoclassical Growth Model." *Review of Economic Studies*, 84(2): 613–649.
- Célerier, Claire, and Adrien Matray.** 2019. "Bank-Branch Supply, Financial Inclusion, and Wealth Accumulation." *Review of Financial Studies*, 32(12): 4767–4809.
- Corbae, Dean, and Pablo D'Erasmus.** 2021. "Capital Buffers in a Quantitative Model of Banking Industry Dynamics." *Econometrica*, 89: 2975–3023.
- Dabla-Norris, Era, Yan Ji, Robert M. Townsend, and D. Filiz Unsal.** 2021. "Distinguishing Constraints on Financial Inclusion and Their Impact on GDP, TFP, and The Distribution of Income." *Journal of Monetary Economics*, 117: 1–18.
- Demirguc-Kunt, Asli, Leora Klapper, Dorothe Singer, Saniya Ansar, and Jake Hess.** 2018. "The Global Findex Database 2017: Measuring Financial Inclusion and the Fintech Revolution." World Bank Group.
- Desmet, Klaus, and Esteban Rossi-Hansberg.** 2014. "Spatial Development." *American Economic Review*, 104(4): 1211–1243.
- Desmet, Klaus, Dávid Krisztián Nagy, and Esteban Rossi-Hansberg.** 2018. "The Geography of Development." *Journal of Political Economy*, 126(3): 903 – 983.
- De Vany, Arthur S.** 1976. "Uncertainty, Waiting Time, and Capacity Utilization: A Stochastic Theory of Product Quality." *Journal of Political Economy*, 84(3): 523–541.
- Doepke, Matthias, and Martin Schneider.** 2006. "Inflation and the Redistribution of Nominal Wealth." *Journal of Political Economy*, 114(6): 1069–1097.
- Dou, Winston, Yan Ji, David Reibstein, and Wei Wu.** 2021. "Inalienable Customer Capital, Corporate Liquidity, and Stock Returns." *The Journal of Finance*, 76(1): 211–265.
- Dou, Winston, Yan Ji, Di Tian, and Pengfei Wang.** 2022. "Asset Pricing with Misallocation." Working Papers.
- Ehrlich, Daniel, and Robert M. Townsend.** 2021. "Spatial Spillovers and Labor Market Dynamics: Village

- Financial Interventions in Thailand.” MIT Working Paper.
- Elliehausen, Gregory E., and John D. Wolken.** 1990. “Banking markets and the use of financial services by small and medium- sized businesses.” *Federal Reserve Bulletin*, , (Oct): 801–817.
- Felkner, John S., and Robert M. Townsend.** 2011. “The Geographic Concentration of Enterprise in Developing Countries.” *The Quarterly Journal of Economics*, 126(4): 2005–2061.
- Fonseca, Julia, and Adrien Matray.** 2022. “The Real Effects of Banking the Poor: Evidence from Brazil.” Working Papers.
- Fry, Maxwell J.** 1986. “Financial structure, financial regulation, and financial reform in the Philippines and Thailand, 1960–1984.” In *Financial Policy and Reform in Pacific Basin Countries*, , ed. H. S. Cheng, 161–84. New York: Lexington Book.
- Fry, Maxwell J.** 1995. *Money, interest, and banking in economic development*. Johns Hopkins University Press.
- Furman, Jason.** 2016. “Financial Inclusion in the United States.” *Council of Economic Advisers Issue Brief*.
- Fuster, Andreas, Greg Kaplan, and Basit Zafar.** 2021. “What Would You Do with \$500? Spending Responses to Gains, Losses, News, and Loans.” *Review of Economic Studies*, , (0): 1–36.
- Gine, Xavier, and Robert M. Townsend.** 2004. “Evaluation of financial liberalization: a general equilibrium model with constrained occupation choice.” *Journal of Development Economics*, 74(2): 269–307.
- Greenstone, Michael, and Rema Hanna.** 2014. “Environmental Regulations, Air and Water Pollution, and Infant Mortality in India.” *American Economic Review*, 104(10): 3038–3072.
- Greenwood, Jeremy, and Boyan Jovanovic.** 1990. “Financial Development, Growth, and the Distribution of Income.” *Journal of Political Economy*, 98(5): 1076–1107.
- Greenwood, Jeremy, Juan M. Sanchez, and Cheng Wang.** 2010. “Financing Development: The Role of Information Costs.” *American Economic Review*, 100(4): 1875–91.
- Greenwood, Jeremy, Juan Sanchez, and Cheng Wang.** 2013. “Quantifying the Impact of Financial Development on Economic Development.” *Review of Economic Dynamics*, 16(1): 194–215.
- Guner, Nezih, Gustavo Ventura, and Xu Yi.** 2008. “Macroeconomic Implications of Size-Dependent Policies.” *Review of Economic Dynamics*, 11(4): 721–744.
- Guvenen, Fatih.** 2011. “Macroeconomics with heterogeneity : a practical guide.” *Economic Quarterly*, 97(3Q): 255–326.
- Guvenen, Fatih, Fatih Karahan, Serdar Ozkan, and Jae Song.** 2015. “What Do Data on Millions of U.S. Workers Reveal about Life-Cycle Earnings Dynamics?” Federal Reserve Bank of New York Staff Reports 710.
- Guvenen, Fatih, Greg Kaplan, Jae Song, and Justin Weidner.** 2017. “Lifetime Incomes in the United States over Six Decades.” National Bureau of Economic Research, Inc NBER Working Papers 23371.
- Heathcote, Jonathan, and Fabrizio Perri.** 2018. “Wealth and Volatility.” *Review of Economic Studies*, 85(4): 2173–2213.
- Heathcote, Jonathan, Kjetil Storesletten, and Giovanni L. Violante.** 2009. “Quantitative Macroeconomics with Heterogeneous Households.” *Annual Review of Economics*, 1(1): 319–354.
- Herkenhoff, Kyle F.** 2019. “The Impact of Consumer Credit Access on Unemployment.” *Review of Economic Studies*, 86(6): 2605–2642.
- Holmes, Thomas J.** 2011. “The Diffusion of Wal-Mart and Economies of Density.” *Econometrica*, 79(1): 253–302.
- Jager, Simon, and Jörg Heining.** 2019. “How Substitutable Are Workers? Evidence from Worker Deaths.” MIT Working Paper.
- Jayaratne, Jith, and Philip E Strahan.** 1996. “The Finance-Growth Nexus: Evidence from Bank Branch Deregulation.” *The Quarterly Journal of Economics*, 111(3): 639–70.
- Jeong, Hyeok, and Robert M. Townsend.** 2008. “Growth And Inequality: Model Evaluation Based On An Estimation-Calibration Strategy.” *Macroeconomic Dynamics*, 12(S2): 231–284.
- Jeong, Hyeok, and Robert M. Townsend.** 2007. “Sources of TFP growth: occupational choice and financial deepening.” *Economic Theory*, 32(1): 179–221.
- Jermann, Urban, and Vincenzo Quadrini.** 2012. “Macroeconomic Effects of Financial Shocks.” *American Economic Review*, 102(1): 238–271.
- Jia, Panle.** 2008. “What Happens When Wal-Mart Comes to Town: An Empirical Analysis of the Discount Retailing Industry.” *Econometrica*, 76(6): 1263–1316.
- Jorgenson, Dale.** 1963. “Capital Theory and Investment Behavior.” *American Economic Review*, 53(2): 247–259.
- Kaboski, Joseph P., and Robert M. Townsend.** 2011. “A Structural Evaluation of a Large-Scale Quasi-Experimental Microfinance Initiative.” *Econometrica*, 79(5): 1357–1406.
- Kaboski, Joseph P., and Robert M. Townsend.** 2012. “The Impact of Credit on Village Economies.” *American Economic Journal: Applied Economics*, 4(2): 98–133.
- Kaplan, Greg, and Giovanni L. Violante.** 2014. “A Model of the Consumption Response to Fiscal Stimulus Payments.” *Econometrica*, 82(4): 1199–1239.
- Kaplan, Greg, and Giovanni L. Violante.** 2018. “Microeconomic Heterogeneity and Macroeconomic Shocks.” *Journal of Economic Perspectives*, 32(3): 167–194.
- Kaplan, Greg, and Guido Menzio.** 2015. “The Morphology Of Price Dispersion.” *International Economic Review*, 56: 1165–1206.
- Kaplan, Greg, and Guido Menzio.** 2016. “Shopping Externalities and Self-Fulfilling Unemployment Fluctua-

- tions." *Journal of Political Economy*, 124(3): 771–825.
- Kaplan, Greg, and Sam Schulhofer-Wohl.** 2017. "Understanding The Long-Run Decline In Interstate Migration." *International Economic Review*, 58(1): 57–94.
- Kaplan, Greg, Benjamin Moll, and Giovanni L. Violante.** 2018. "Monetary Policy According to HANK." *American Economic Review*, 108(3): 697–743.
- Kaplan, Greg, Giovanni L. Violante, and Justin Weidner.** 2014. "The Wealthy Hand-to-Mouth." *Brookings Papers on Economic Activity*, 45(1 (Spring)): 77–153.
- Kaplan, Greg, Guido Menzio, Leena Rudanko, and Nicholas Trachter.** 2019. "Relative Price Dispersion: Evidence and Theory." *American Economic Journal: Microeconomics*, 11(3): 68–124.
- Kaplan, Greg, Kurt Mitman, and Giovanni L. Violante.** 2020. "The Housing Boom and Bust: Model Meets Evidence." *Journal of Political Economy*, 128(9): 3285–3345.
- Karlan, Dean, and Jonathan Zinman.** 2009. "Observing Unobservables: Identifying Information Asymmetries With a Consumer Credit Field Experiment." *Econometrica*, 77(6): 1993–2008.
- Kennan, John, and James R. Walker.** 2011. "The Effect of Expected Income on Individual Migration Decisions." *Econometrica*, 79(1): 211–251.
- Kerr, William R., and Ramana Nanda.** 2009. "Democratizing entry: Banking deregulations, financing constraints, and entrepreneurship." *Journal of Financial Economics*, 94(1): 124–149.
- King, Robert G., and Ross Levine.** 1994. "Capital fundamentalism, economic development, and economic growth." *Carnegie-Rochester Conference Series on Public Policy*, 40(1): 259–292.
- Kleinman, Benny, Ernest Liu, and Stephen J. Redding.** 2021. "Dynamic Spatial General Equilibrium." Princeton University. Economics Department. Working Papers 2021-31.
- Lagakos, David, Ahmed Mobarak, and Michael Waugh.** 2020. "The Welfare Effects of Encouraging Rural-Urban Migration." National Bureau of Economic Research, Inc NBER Working Papers 24193.
- Lagakos, David, Samuel Marshall, Ahmed Mobarak, Corey Vernot, and Michael Waugh.** 2020. "Migration costs and observational returns to migration in the developing world." *Journal of Monetary Economics*, 113(C): 138–154.
- Lloyd-Ellis, Huw, and Dan Bernhardt.** 2000. "Enterprise, Inequality and Economic Development." *Review of Economic Studies*, 67(1): 147–68.
- Lucas, Robert E.** 1978. "On the Size Distribution of Business Firms." *Bell Journal of Economics*, 9(2): 508–523.
- Menzio, Guido, and Nicholas Trachter.** 2015. "Equilibrium price dispersion with sequential search." *Journal of Economic Theory*, 160(C): 188–215.
- Menzio, Guido, and Nicholas Trachter.** 2018. "Equilibrium Price Dispersion Across and Within Stores." *Review of Economic Dynamics*, 28: 205–220.
- Mian, Atif, Kamallesh Rao, and Amir Sufi.** 2013. "Household Balance Sheets, Consumption, and the Economic Slump." *The Quarterly Journal of Economics*, 128(4): 1687–1726.
- Midrigan, Virgiliu, and Daniel Yi Xu.** 2014. "Finance and Misallocation: Evidence from Plant-Level Data." *American Economic Review*, 104(2): 422–458.
- Miller, Merton H., and Daniel Orr.** 1966. "A Model of the Demand for Money by Firms." *The Quarterly Journal of Economics*, 80(3): 413–435.
- Moll, Benjamin.** 2014. "Productivity Losses from Financial Frictions: Can Self-Financing Undo Capital Misallocation?" *American Economic Review*, 104(10): 3186–3221.
- Moll, Benjamin, Robert Townsend, and Victor Zhorin.** 2017. "Economic Development, Flow of Funds and the Equilibrium Interaction of Financial Frictions." *Proceedings of the National Academy of Sciences*, 114(24): 6176–6184.
- Monte, Ferdinando, Stephen J. Redding, and Esteban Rossi-Hansberg.** 2018. "Commuting, Migration, and Local Employment Elasticities." *American Economic Review*, 108(12): 3855–3890.
- Morten, Melanie.** 2019. "Temporary Migration and Endogenous Risk Sharing in Village India." *Journal of Political Economy*, 127(1): 1–46.
- Munshi, Kaivan, and Mark Rosenzweig.** 2016. "Networks and Misallocation: Insurance, Migration, and the Rural-Urban Wage Gap." *American Economic Review*, 106(1): 46–98.
- Nguyen, Hoai-Luu Q.** 2019. "Are Credit Markets Still Local? Evidence from Bank Branch Closings." *American Economic Journal: Applied Economics*, 11(1): 1–32.
- Okuda, Hidenobu, and Fumiharu Mieno.** 1999. "What Happened to Thai Commercial Banks in The Pre-Asian Crisis Period: Microeconomic Analysis of Thai Banking Industry." *Hitotsubashi Journal of Economics*, (40): 97 – 121.
- Paweenawat, Archawa, and Robert M. Townsend.** 2019. "The Impact of Regional Isolationism: Disentangling Real and Financial Factors." Department of Economics, MIT Working paper.
- Petersen, Mitchell A., and Raghuram Rajan.** 2002. "Does Distance Still Matter? The Information Revolution in Small Business Lending." *Journal of Finance*, 57(6): 2533–2570.
- Pitt, Mark M., and Shahidur R. Khandker.** 1998. "The Impact of Group-Based Credit Programs on Poor Households in Bangladesh: Does the Gender of Participants Matter?" *Journal of Political Economy*, 106(5): 958–996.
- Quadrini, Vincenzo.** 2000. "Entrepreneurship, Saving and Social Mobility." *Review of Economic Dynamics*,

- 3(1): 1–40.
- Redding, Stephen J., and Esteban Rossi-Hansberg.** 2017. “Quantitative Spatial Economics.” *Annual Review of Economics*, 9(1): 21–58.
- Samphantharak, Krislert, and Robert M. Townsend.** 2009. *Households as Corporate Firms*. Cambridge University Press.
- Samphantharak, Krislert, and Robert M. Townsend.** 2018. “Risk and Return in Village Economies.” *American Economic Journal: Microeconomics*, 10(1): 1–40.
- Skully, Michael T.** 1984. “Financial Institutions and Markets in Thailand.” In *Financial Institutions and Markets in Southeast Asia*. Vol. 6, , ed. Michael T. Skully, 296–374. Hong Kong: Macmillan.
- Smith, Matthew, Danny Yagan, Owen Zidar, and Eric Zwick.** 2019. “Capitalists in the Twenty-First Century.” *The Quarterly Journal of Economics*, 134(4): 1675–1745.
- Stein, Luke, and Constantine Yannelis.** 2020. “Financial Inclusion, Human Capital, and Wealth Accumulation: Evidence from the Freedman’s Savings Bank.” *Review of Financial Studies*, 33(11): 5333–5377.
- Tobin, James.** 1956. “The Interest Elasticity of the Transactions Demand for Cash.” *Review of Economics and Statistics*, 66: 241–247.
- Tombe, Trevor, and Xiaodong Zhu.** 2019. “Trade, Migration, and Productivity: A Quantitative Analysis of China.” *American Economic Review*, 109(5): 1843–72.
- Townsend, Robert M.** 1983. “Financial Structure and Economic Activity.” *American Economic Review*, 73: 895–911.
- Townsend, Robert M.** 2011. *Financial Systems in Developing Economies: Growth, Inequality and Policy Evaluation in Thailand*. Oxford University Press.
- Townsend, Robert M., and Kenichi Ueda.** 2006. “Financial Deepening, Inequality, and Growth: A Model-Based Quantitative Evaluation.” *Review of Economic Studies*, 73(1): 251–293.
- Townsend, Robert M., and Kenichi Ueda.** 2010. “Welfare Gains From Financial Liberalization.” *International Economic Review*, 51(3): 553–597.
- Wang, Olivier.** 2020. “Banks, low interest rates, and monetary policy transmission.” New York University Working Paper.