

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

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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.

I. Introduction

Implementing financial sector policies that promote financial inclusion and growth is one of the key goals of developing economies. Often, these

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

Electronically published June 27, 2023

Journal of Political Economy, volume 131, number 8, August 2023.

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<https://doi.org/10.1086/724112>

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 United States 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 1986–96 period. As a result of 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.

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 Massachusetts Institute of Technology, Michigan State University, the University of California Los Angeles, Hong Kong University of Science and Technology, Central University of Finance and Economics, the Workshop on Finance and Development, the Society for the Advancement of Economic Theory, the Roundtable on Central Banking and Inequality, the North American Summer Meeting of the Econometric Society, the Asian Meeting of the Econometric Society, the Society for Economic Dynamics, the Australian Meeting of the Econometric Society, and the China International Conference in Macroeconomics for their comments and suggestions. Ji is grateful for the financial support of a Hong Kong Research Grants Council General Research Fund grant (project no. 16500718). Townsend gratefully acknowledges research support from the Eunice Kennedy Shriver National Institute of Child Health and Human Development (grant no. R01 HD027638), the Centre for Economic Policy Research, and the Department for International Development under grant MRG002_1255. This paper was edited by Greg Kaplan.

¹ In the United States, about 30% of the poor are unbanked (Célerier 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).

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 the two have opposite implications for income inequality.

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

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

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 micro foundations 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 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 on the basis of 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 on the basis of the residual value of a cross-sectional regression that 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 1987–96 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 northeast 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 because of

³ In app. 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.

its large impacts on local income, whereas the deposit channel slightly increases cross-market income inequality because of 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 as a result of 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, further facilitating wealth accumulation. By contrast, subsidizing branches generates only 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 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, on the basis of 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 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

⁴ See, e.g., Banerjee and Newman (1993); Lloyd-Ellis and Bernhardt (2000); Quadrini (2000); Gine and Townsend (2004); Cagetti and De 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); and 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). In recent work, 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.

⁵ There 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 networks and its implication for credit flows across locations, but they do not consider dynamic branch location choice or potential general equilibrium effects.

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 that of 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; Guvenen 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 section II. The model is described in section III and calibrated in section IV. In section V, we evaluate the model's prediction on branch locations, shedding light on the role played by different market characteristics. In section VI, we evaluate the aggregate

⁶ See Redding and Rossi-Hansberg (2017) for a comprehensive review.

⁷ Our 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 interregional trade.

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

and distributional impacts of bank expansion through the lens of the model. In section VII, we apply the model to analyze policy counterfactuals. Finally, section VIII concludes.

II. 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 1986–96, 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 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

⁹ We exclude the 1997 crisis from our analysis and examine the growth period before the crisis because we want to understand the endogenous links between financial deepening, growth, and inequality across regions. In app. 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.

¹⁰ For example, the *International Financial Statistics* 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.

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. Figure 1A 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 fig. 1B).

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.

A. 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 junctures are connected by seven types

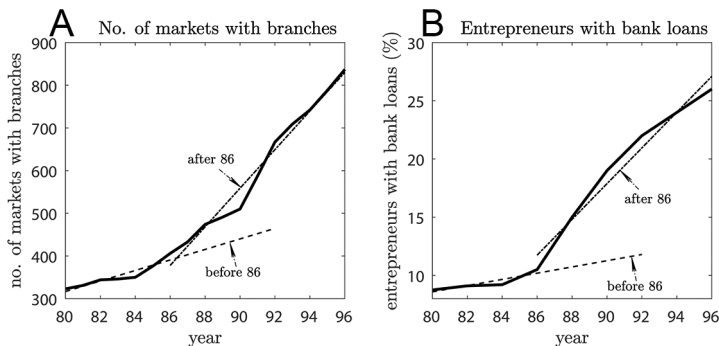


FIG. 1.—Bank branches and credit access in Thailand, 1980–96. *A*, Number of markets with at least one commercial bank branch, using data from the Bank of Thailand and various other financial institutions. Markets are defined and constructed in section II.B. *B*, Fraction of entrepreneurs with access to bank loans, obtained from the Thai Socio-Economic Survey. In each figure, the dashed line is a linear curve fitting the data points between 1980 and 1986, to capture the trend before 1986; and the dash-dotted line is a linear curve fitting the data points between 1986 and 1996, to capture the trend after 1986.

of roads. We estimate the average vehicle speed for each type of road on the basis of real-time information and obtain the car travel time for every road segment (see app. 1.1). The road network remains largely unchanged for our study period, 1986–96.¹¹ Commercial bank branch locations in each year are constructed with data from the Bank of Thailand.¹²

B. 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 1986–96, 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, on which basis 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 sec. III). In figure 2A, 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. Figure 2B presents our model economy (see sec. III), which consists of the local spatial markets corresponding to the branch locations in figure 2A. These markets are connected via road links, forming a network.

¹¹ Felkner 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 app. 1.1.

¹² Our 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.

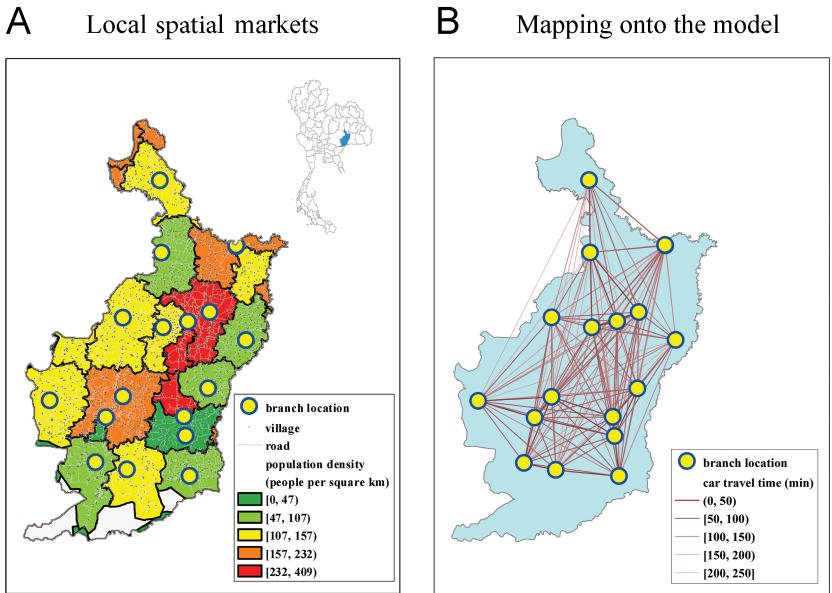


FIG. 2.—Illustration of local spatial markets based on GIS data and the model. *A*, Local spatial markets, based on GIS data for Buriram Province in Thailand. The yellow nodes represent commercial bank branch locations, and the small gray dots represent villages. The black lines represent the borders 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. *B*, Buriram Province in our model economy (see sec. III). The yellow nodes correspond to the local spatial markets that enclose the branch locations in *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.

C. 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 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 app. 1.2 for details).

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 because of 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., Jäger and Heining 2019; Smith et al. 2019; Fonseca and Matray 2022). Specifically, we base our empirical estimation on the 1986–96 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 includes only 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 III, 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

¹³ In app. 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 sec. III. 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.

scores before the treatment. Guided by our model, we estimate the propensity score on the basis of 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 consisting of treatment and matched control markets, balanced in terms of the covariates (see table OA.2 [in app. 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 Jäger and Heining (2019), we run the following regression:

$$y_{it} = \sum_{\tau=-3}^2 \alpha_{\tau} \times D_{it}^{\tau} \times \text{Treated}_i + \sum_{\tau=-3}^2 \beta_{\tau} D_{it}^{\tau} + \mu_i + \epsilon_{it}, \quad (1)$$

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 (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 (1), captures whether the market is treated (i.e., whether a branch is opened between 1987 and 1996), so we have $\text{Treated}_i = 1$ and $\text{Treated}_{\bar{i}} = 0$. The dummy variable D_{it}^{τ} , which appears in the first and second terms of equation (1), is identical for market i and its matched control market \bar{i} . Specifically, both D_{it} and $D_{i\bar{t}}$ 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 $D_{it}^{\tau} = D_{i\bar{t}}^{\tau} = 1$ 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

¹⁴ The 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 sec. V.B, 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 1987–96 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 app. 2.2).

¹⁵ The 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.

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 μ_i) captures market fixed effects.¹⁶

2. Empirical Results

Table 1 presents the results. Columns 1 and 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 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. Because of 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 radii of 3–5 km, which is another factor explaining why the first branch openings have such economically significant local effects.

Columns 3 and 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

¹⁶ Equation (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.

¹⁷ In our empirical setting, the stable-unit-treatment-value assumption is likely not satisfied because of the spillover effects of branch openings on nearby regions, as indicated by the model developed in sec. III. Thus, rather than interpreting these estimates as capturing the treatment effect on the treated, it is more appropriate to interpret them as capturing the treatment effect on the treated relative to that on the control.

¹⁸ Using 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

	ln(Employment) (1)	ln(Income per capita) (2)	Fraction of Entrepreneurs (3)	Fraction of HH with Bank Loans (4)
$\hat{\alpha}_{-3}$	-.043 (.103)	-.071 (.104)	-.012 (.016)	-.006 (.012)
$\hat{\alpha}_{-2}$	-.013 (.097)	-.009 (.088)	-.001 (.015)	-.007 (.011)
$\hat{\alpha}_0$.186 (.092)	.174 (.089)	.023 (.013)	.034 (.009)
$\hat{\alpha}_1$.305 (.104)	.294 (.094)	.035 (.016)	.039 (.011)
$\hat{\alpha}_2$.341 (.115)	.324 (.102)	.040 (.015)	.038 (.012)
Branch openings	423	400	393	434
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 (eq. [1]) on matched pairs of treatment and control markets. The matching procedure is based on market-level propensity scores. The dependent variables in cols. 1–4 are market-level log employment, log income per capita, the fraction of entrepreneurs, and the fraction of households (HH) 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.

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%. 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 that 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); see, for example, 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 (gross domestic product). Nguyen (2019) estimates large negative local effects of branch closings in the United States. 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 zero 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 appendixes 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.

III. 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).

A. 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 III.B.

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 III.C. The three market characteristics play important roles in aligning the model-implied branch locations with those in the data (see sec. V.B).

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, that is, $\Pi_{i,t} < h$.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 ; that is, $\Psi_t = \{i : B_{i,t} = 1, i \in \mathcal{C}\}$. The set Ψ_t evolves endogenously as a result of 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

$$d_{i,t} = \min\{\tau_{ij} : j \in \Psi_t, \Pi_{j,t} < h\}. \quad (2)$$

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 .

B. Households

1. 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_b , cash m_b , deposits a_b , and the market i in which they live. For brevity, in the rest of this section, we omit the index for an individual household.

¹⁹ For 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.

Talent z_i follows an exogenous stochastic process. With probability γ , households retain their talent from the previous period, that is, $z_i = z_{i-1}$, and with probability $1 - \gamma$, households draw new talent z_i 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_i and deposits a_i 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_i and capital k_i using cash m_i , but they cannot use deposits a_i to do so.²⁰ The trade-off between the two saving instruments is that cash earns no return, whereas deposits earn the interest rate $r_i > 0$ 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 trade-off between cash m_i and deposits a_i is highly reminiscent of the main insight 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 (1986–96), the transportation costs to bank branches in Thailand are important because of the lack of online banking and the government's restrictions on the operation of ATMs (automated teller machines). 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

²⁰ Because 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, 2018; Kaplan and Menzio 2016).

²¹ As 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.

²² Transportation 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).

that geographic proximity to bank branches matters. For example, Célerier and Matray (2019) exploit the US 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 appendix 3.3.3, we show that the average deposit-cash ratio (a_i/m_i) in market i decreases with $d_{i,t}$ in our model, and in 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 United States but not in developing countries. As in Kaplan and Violante (2014), households choose consumption after making portfolio adjustments within each period. This timing assumption implies that our model does not feature a cash-in-advance constraint.

2. Preferences

Households derive utility from consumption c_t and have the following preferences:

$$\mathbb{E}_t \left[\sum_{t'=t}^{\infty} \beta^{t'-t} \frac{c_{t'}^{1-\sigma}}{1-\sigma} \right], \quad (3)$$

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

²³ Studies 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).

²⁴ Such 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).

3. 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 $q_i(k_t, l_t, z_t)$,

$$q_i(k_t, l_t, z_t) = Z_i z_t (k_t^\alpha l_t^{1-\alpha})^{1-\nu}, \quad (4)$$

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 macrofinance 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.

4. 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.

²⁵ The assumption of frictionless capital adjustment affects the model's quantitative implications for the deposit channel (i.e., the reduction in $\xi_{i,t}$) of bank expansion as well as the calibration of $\xi_{i,t}$. In sec. VI.A, 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.

There is limited participation in the credit market. To obtain a loan, entrepreneurs need to pay an up-front 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 2023; 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 farther away from bank branches. The distance-dependent credit entry costs $\psi(\cdot)$ can be due to both transportation and information costs. During our 1986–96 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 require 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 United States, 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

²⁶ A 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

$$\xi k_t \leq m_t + a_t - \psi_{i,t}. \quad (5)$$

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 (5) because it is incurred after production, when households make portfolio adjustments at the end of the period (see fig. 3).

5. Migration

One of our main goals is to develop a macro model that emphasizes spatial heterogeneity. Thus, it is natural and important to allow intermarket migration. Although our focus is on bank expansion, our calibration matches the migration flows in the data (see sec. IV). The role of migration is discussed and separately quantified in 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 et al. 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

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 (eq. [5]).

²⁷ We 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 (2023) assume that migration is subject to a pecuniary cost, a utility cost, and idiosyncratic taste shocks. Kaplan and Schulhofer-Wohl (2017) and Lagakos, Mobarak, and Waugh (2023) 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, for tractability, Ehrlich and Townsend (2021) assume that migration decisions are made at the end of the period.

²⁸ Kennan 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 fig. OA.28 (app. 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.

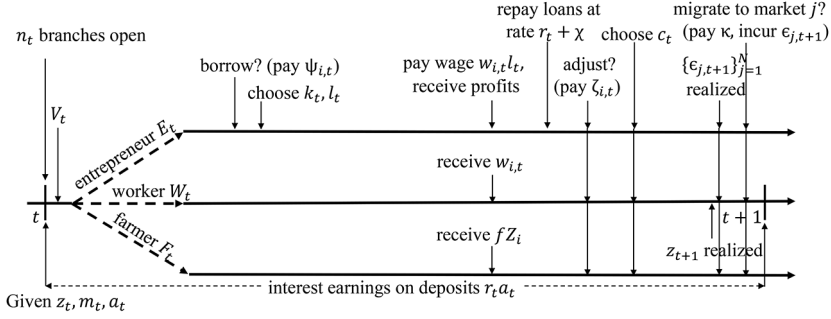


FIG. 3.—Timing of events.

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 2023), 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 .

6. 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 sec. III.C). 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 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,

$$V_t(s_t, i) = \max\{F_t(s_t, i), W_t(s_t, i), E_t(s_t, i)\}. \quad (6)$$

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

$$F_t^0(s_t, i) = \max_{c_t, m_{t+1}} \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_t \left[\max_{j \in \{1, \dots, N\}} \{V_{t+1}(s_{t+1}, j) + \epsilon_{j,t+1}\} \right] \right\}, \quad (7)$$

$$\text{subject to } m_{t+1} + c_t = m_t + fZ_i - \kappa \mathbf{1}_{\{j \neq i\}}, \quad (8)$$

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

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 eq. [8] 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 fig. 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 a single equation that determines the evolution of total wealth $m_t + a_t$. The value $F_t^1(s_t, i)$ is given by

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

$$\text{subject to } m_{t+1} + a_{t+1} + c_t = m_t + (1 + r_t)a_t - \zeta_{i,t} + fZ_i \quad (9)$$

$$- \kappa \mathbf{1}_{\{j \neq i\}}, \text{ with } c_t, m_{t+1}, a_{t+1} \geq 0,$$

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

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

If households choose to be workers, their value $W_i(s_b, i)$ is determined by solving a problem similar to the farmers', except that the subsistence income fZ_i is replaced with the equilibrium local wage $w_{i,t}$ in market i . We present the worker problem in 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 $\psi_{i,b}$, bank expansion can generate local wage takeoffs across markets.

Finally, the value function of entrepreneurs is

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

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 $E_t^{00}(s_t, i)$:

$$E_t^{00}(s_t, i) = \max_{c, k_t, l_t, m_{t+1}} \left\{ \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_t \left[\max_{j \in \{1, \dots, N\}} \{V_{t+1}(s_{t+1}, j) + \epsilon_{j,t+1}\} \right] \right\},$$

subject to

$$\begin{aligned} m_{t+1} + c_t &= m_t - k_t + Z_i z_t (k_t^\alpha l_t^{1-\alpha})^{1-\nu} + (1 - \delta)k_t - w_{i,t}l_t - \kappa \mathbf{1}_{\{j \neq i\}}, \\ k_t &\leq m_t, \\ a_{t+1} &= (1 + r_t)a_t, \text{ with } c_t, m_{t+1} \geq 0. \end{aligned} \quad (11)$$

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 $E_t^{11}(s_t, i)$:

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

subject to

$$\begin{aligned} m_{t+1} + a_{t+1} + c_t &= -[1 + (r_t + \chi) \mathbf{1}_{\{k_t \geq m_t\}}][k_t - (m_t - \psi_{i,t})] + (1 + r_t)a_t \\ &\quad - \zeta_{i,t} + Z_t z_t (k_t^\alpha l_t^{1-\alpha})^{1-\nu} + (1 - \delta)k_t - w_{i,t}l_t - \kappa \mathbf{1}_{\{j \neq i\}}, \\ k_t &\leq (m_t + a_t - \psi_{i,t})/\xi, \text{ with } c_t, m_{t+1}, a_{t+1} \geq 0, \end{aligned} \quad (12)$$

where $\mathbf{1}_{\{k_t \geq m_t\}}$ 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 appendix 3.1.

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

7. 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 app. 3.2 for the derivation):

$$\omega_{i,t}(s_t, i) = \mathbb{E}_t \left[\frac{\exp(V_{t+1}(s_{t+1}, i'))^{1/\eta}}{\sum_{j=1}^N \exp(V_{t+1}(s_{t+1}, j))^{1/\eta}} \middle| s_t, i \right], \quad (13)$$

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

Equation (13) 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 $i' \neq i$ (because of 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., $\Pi_{i,t}$, $Z_{i,t}$, $d_{i,t}$) jointly determine households' occupation choice, credit access, and portfolio adjustment

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

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, which we discuss in appendix 3.3.4.

Using equation (13), the continuation value in the household problem (eqq. [7], [9], [11], [12]) can be simplified to

$$\mathbb{E}_t \left[\max_{j \in \{1, \dots, N\}} \{ V_{t+1}(s_{t+1}, j) + \epsilon_{j,t+1} \} \right] = \mathbb{E}_t \left[\eta \log \left(\sum_{j=1}^N \exp (V_{t+1}(s_{t+1}, j))^{1/\eta} \right) \right], \quad (14)$$

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

C. 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 sec. IV). 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,

$$\max_{\{\Lambda_t\}_{t=1}^{\infty}} \sum_{t=1}^{\infty} \left(\sum_{i \in \Lambda_t} \Theta_{i,t} \right) + \sum_{i \in \Psi_0} \Theta_{i,0}, \quad (15)$$

$$\text{subject to } \Lambda_t \subset \Psi_{t-1}^C \text{ and } |\Lambda_t| = n_t \text{ for all } t \geq 1, \quad (16)$$

$$\Psi_t = \Psi_{t-1} \cup \Lambda_t \text{ for all } t \geq 1, \quad (17)$$

where the first term in the objective function (15) 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 eq. [18]). 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 (16) 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 (17) 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 (eq. [15]).

³¹ The 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.

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 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

$$\Theta_{i,t} = \chi \sum_{t'=t}^{\infty} \beta^{t'} \left[X_{i,t'} + \sum_{j \in \{j: d_{j,t'} = \tau_{ij}\}} X_{j,t'} \right]. \quad (18)$$

In equation (18), the total amount of loans made by the branch opened in market i has two components. First, the term $X_{i,t'}$ captures the loans offered to local entrepreneurs in market i at time t' , defined in equation (20). The term $\sum_{j \in \{j: d_{j,t'} = \tau_{ij}\}} X_{j,t'}$ captures loans due to spatial spillovers, that is, 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 $d_{i,t'}$ falling below τ_{ij} for some market j . As we show in appendix 3.7.2, because branch locations are chosen to maximize profits (eq. [15]), branches tend to be opened in markets with higher $\Pi_{i,t}$ or higher Z_i or in markets that can serve households in nearby markets.

One way to interpret problem (15) 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)

³² Our 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 1986–96 period, recent data indicate that our assumption is reasonable. In 2005, the Bank of Thailand introduced the Bangkok Interbank Offered Rate, 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 2005–20, 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.

³³ For 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 $\binom{N}{n} = N! / ((N-n)! n!)$ 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 $\prod_{i=1}^n (N-i+1) = N! / (N-n)!$ possible combinations.

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 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-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, Assunção, Mityakov, and Townsend (2020) document that the BAAC deliberately yields ground to the expansion of the commercial banking sector in Thailand. Such antipreemptive behavior can be partly rationalized in their model by assuming that the BAAC considers joint profit maximization in choosing branch locations. Assunção, Mityakov, and Townsend (2020) show that their baseline oligopoly model implies patterns of financial access similar to those of the model 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 (18), 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 (15), the central authority is forward looking and internalizes such spatial spillovers and cannibalization across branches, not only for branches opened in the same period 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 (15) 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 app. 5). In brief, we break the location choice of branches across the country into a set of smaller

³⁴ To maintain tractability, Assunção, Mityakov, 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 app. 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.

problems that focus on specific segments of the country. These segments are constructed with 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.

D. Equilibrium and Aggregation

Figure 4 presents the circular flow of our model to facilitate discussion of the equilibrium. Denote by $\phi_i(s|i)$ 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 (6)–(12) 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 (15).
- iii) The equilibrium interest rate r_t is determined by the economy-wide loan-market-clearing condition at time t :

$$\sum_{i=1}^N \Pi_{i,t} \int a \phi_t(s|i) ds = \sum_{i=1}^N X_{i,t}, \quad (19)$$

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

$$X_{i,t} = \Pi_{i,t} \int [k_t(s, i) - (m - \psi_{i,t})] \mathbf{1}_{\{k_t(s, i) \geq m\}} \phi_t(s|i) ds, \quad (20)$$

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

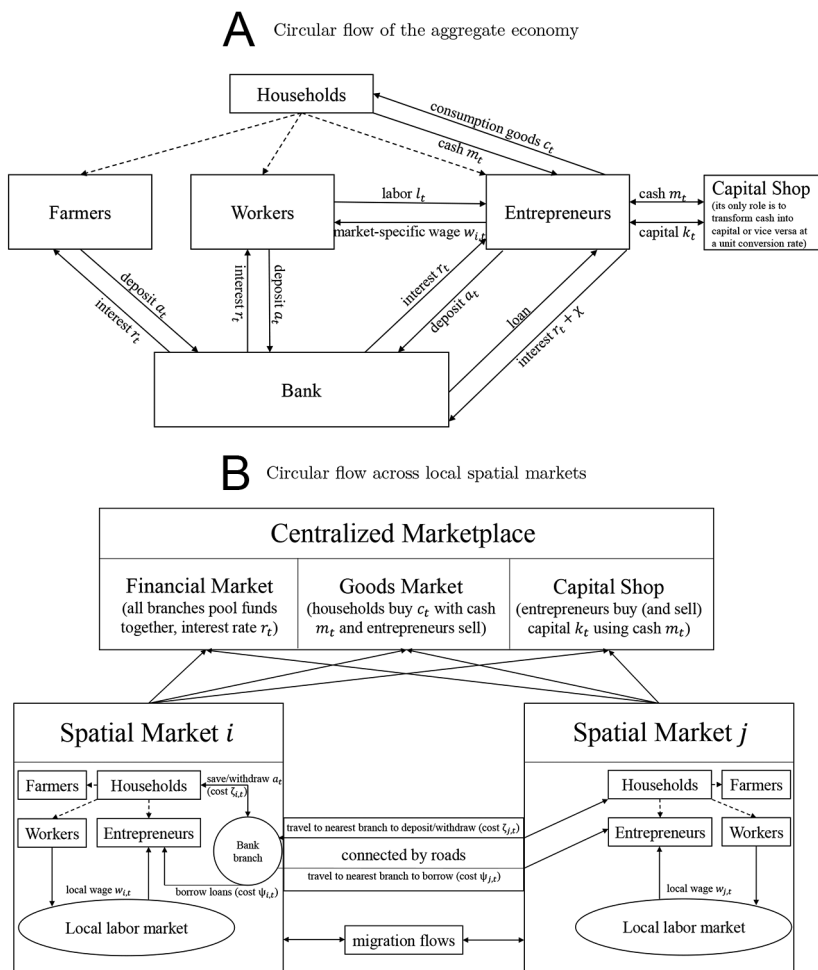


FIG. 4.—Circular flow of the model.

- 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 $\int l_t(s, i) \phi_i(s|i) ds$ is lower than the measure of nonentrepreneurs $\int \mathbf{1}_{\{V_t(s, i) > E_t(s, i)\}} \phi_i(s|i) ds$ 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 :

$$\int \mathbf{1}_{\{V_t(s, i) > E_t(s, i)\}} \phi_i(s|i) ds = \int l_t(s, i) \phi_i(s|i) ds. \quad (21)$$

- v) The size of each market $i \in \mathcal{C}$ evolves according to migration flow equation (13):

$$\Pi_{i,t+1} = \sum_{j=1}^N \Pi_{j,t} \int \omega_{i,t}(s, j) \phi_t(s|j) ds, \quad (22)$$

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_b consisting of markets with branches, evolves according to equation (17).

IV. 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 (fig. 6A).

Below, we first calibrate the characteristics of the local spatial markets for the initial year, 1986, in section IV.A. We then calibrate the model's parameters, which are either determined from external information without simulating the model (sec. IV.B) or calibrated internally from moment matching (sec. IV.C). Finally, in section IV.D, we validate the model-implied dynamic effects of branch openings at the market level against our empirical estimates in table 1.

A. Market Heterogeneity

Figure OA.3 (in app. 1.2) displays the values for the three dimensions of market heterogeneity, $\Pi_{i,b}$, $d_{i,b}$ 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 app. 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

³⁵ To 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 app. 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, 1986–96.

density in 1986.³⁶ The evolution of $\Pi_{i,t}$ for $t > 0$ is determined by equation (22).

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 (17). 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 (2).

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:

$$\ln(Y_i) = \alpha + \beta_1 \ln(K_i) + \beta_2 B_i + \epsilon_i, \quad (23)$$

where $\ln(Y_i)$ and $\ln(K_i)$ are the log income per capita and log capital stock per capita, respectively, of market i ; B_i is a dummy variable indicating whether market i has a branch in 1986. The predicted value $\exp(\beta_1 \ln(K_i) + \hat{\beta}_2 B_i)$ 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; that is, $\bar{Z} \equiv \sum_{i=1}^N Z_i \Pi_{i,0} / \sum_{i=1}^N \Pi_{i,0} = 1$.³⁸

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

³⁷ As 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 (23) 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.

³⁸ To 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 app. 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

B. *Externally Determined Parameters*

Several parameters are calibrated externally without simulating the model (see panel A of table 2). 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 1986–96 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 appendix 3.7.3.

C. *Internally Calibrated Parameters*

The remaining parameters are calibrated by matching relevant moments (see panel B of table 2). We first solve and simulate the entire transition path for the 1986–96 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 must 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.

1. 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

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

A. Externally Determined Parameters		
Parameter	Symbol	Value
Risk aversion	σ	1.5
Return to scale	ν	.14
Interest rate spread (%)	χ	4.82
Capital share	α	.33
Depreciation rate	δ	.08
Branch capacity	h	150
B. Internally Calibrated Parameters		
Parameter	Symbol	Value
Discount rate	β	.89
Subsistence income	f	.77
Fixed migration cost	κ	2.2
Idiosyncratic taste dispersion	η	.008
Portfolio adjustment cost	ζ	.1
Sensitivity of $\zeta_{i,t}$ to distance	θ_{ζ}	.0015
Credit entry cost	ψ	.83
Sensitivity of $\psi_{i,t}$ to distance	θ_{ψ}	.215
Liquidation loss rate	ξ	.59
Tail of talent distribution	ρ	4.7
Persistence of talent	γ	.72
Moments	Data	Model
Interest rate in 1986 (%)	8.3	8.3
Fraction of farmers in 1986 (%)	46	46
Migration rate, 1986–96 (%)	4.7	4.7
Out-migrant share ratio	.89	.89
Average deposit-cash ratio	27	27
Sensitivity of deposit-cash ratio to $d_{i,t}$	−1.07	−1.05
Fraction of households with loans (%)	1.63	1.63
DID estimate ($\hat{\alpha}_0$) for credit access	.034	.031
DID estimate ($\hat{\alpha}_0$) for employment	.186	.196
std($\Delta \log(\text{revenue})$)	.58	.58
AC1 of $\log(\text{revenue})$.86	.88
AC3 of $\log(\text{revenue})$.77	.73
AC5 of $\log(\text{revenue})$.71	.63

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: the standard deviation of log revenue growth and the autocorrelations 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 appendix 4.3.4, we discuss the sensitivity of our model’s quantitative implications to these two parameters.

2. 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 app. 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 1986–96 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 1986–96, 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 1986–96 period. The parameter η determines migration decisions for idiosyncratic reasons. In figure OA.23 (app. 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.

3. Credit Entry and Portfolio Adjustment Costs

Because $\psi_{i,t}$ and $\xi_{i,t}$ are not directly observable, we calibrate their values through parametric indirect inference. We assume that both $\psi_{i,t}$ and $\xi_{i,t}$

³⁹ A 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 three to eight townships, as defined in sec. II.B. 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 trade-off 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 that 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).

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 III.B, $\psi_{i,t}$ 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 (1) in the simulated data to estimate the causal impact of branch openings on the local fraction of households with bank loans (see sec. IV.D). 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 col. 4 of table 1). In 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 (app. 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 appendix 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 $d_{i,t}$

⁴⁰ We 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 because of 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.

⁴¹ In 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. High calibrated costs are not uncommon in the literature: e.g., Townsend and Ueda (2006, n. 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.

has the same effect on $\psi_{i,t}$ and on $\xi_{i,t}$) generate very similar quantitative implications of bank expansion, although the relative importance of the underlying credit and deposit channels varies.

4. 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 (1) aligns with the estimate in the data ($\hat{\alpha}_0$ in col. 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 unsecured loans with no collateral requirements are excluded. In 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.

D. 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 (1), using simulated data, where treatment and control markets are matched by their propensity scores. When estimating propensity scores, we use covariates $\Pi_{i,b}$, $d_{i,b}$, and Z_b , which fully summarize market heterogeneity in our model.

Figure 5 compares the market-level effects of branch openings in the model (solid lines) and the data (dashed lines). Our calibration in section IV.C targets only the two point estimates, $\hat{\alpha}_0$, in figures 5A and 5B, 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. Figures 5C and 5D show that the model-implied effects of branch openings on local income per capita and the

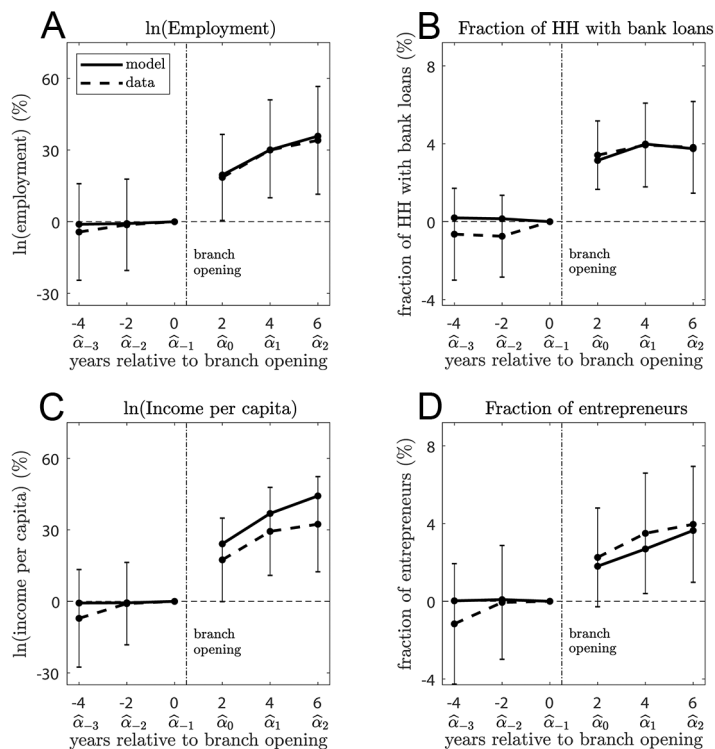


FIG. 5.—Dynamic effects of branch openings at the market level. The dashed lines visualize the empirical estimates in table 1, in which all coefficients are normalized relative to $\tau = -1$. The vertical bars represent the corresponding 95% confidence intervals. The solid lines represent the model-implied 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 $t = 2$. HH = households.

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

V. Model Prediction on Branch Locations

In this section, we examine the model's predictions on the placement of 431 new branches opened during the 1987–96 period. Of the 1,428 markets defined in section II.B, 406 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 section V.A, we first study the model's ability to capture the overall geographic patterns of new branch openings, and in section V.B, we evaluate the model's predictive power for the locations of these branches, elucidating the relative importance of each market characteristic.

A. 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 app. 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 Walmart stores and finds that new stores are always located close to existing stores; Walmart never jumps to some far-off location, intending to fill the gap between stores later. The main reason for Walmart's strategy, as suggested by Holmes (2011), is that it gains logistic benefits by operating its stores close to each other. Products sold by Walmart are supplied by regional distribution centers. When stores are opened close to a distribution center, Walmart 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 sec. III.C). 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 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 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 north-east 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 (fig. 6A), the number of new branches opened in each region implied by our model is quite similar to the data (fig. 6B–6F). 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 (fig. 6B), the model captures the initial decline in the number of new branch openings during 1987–90 but predicts a significant increase in 1991, which is 1 year earlier than the increase in the data. In the central region (fig. 6C), the model captures the trend very well except for the last 2 years of the study period. In the north region (fig. 6D), 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

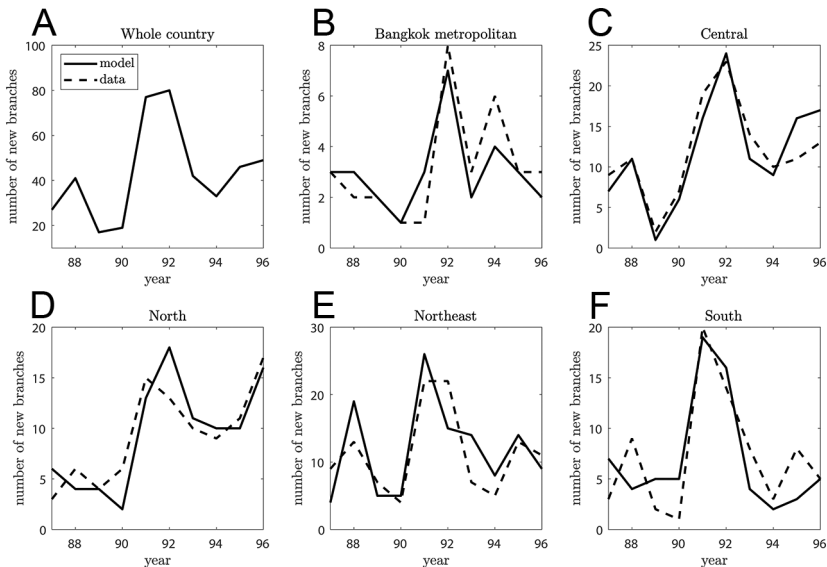


FIG. 6.—Branches opened in different regions, 1987–96. A illustrates that our calibration exogenously specifies the number of new branches opened each year in the whole country. B–F compare the number of new branches opened in different regions. The total number of branches opened in each region in the model and the data, respectively, are as follows: Bangkok: 30 and 32; central: 118 and 119; north: 94 and 94; northeast: 119 and 113; and south: 70 and 73. For details, see table OA.11 (app. 3.7.5).

and south regions (figs. 6E and 6F, respectively), the model largely captures the ups and downs in the data.

B. 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 1987–96 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

TABLE 3
MODEL PREDICTION FOR THE PLACEMENT OF BRANCHES

	BASELINE (1)	$\tau_{ij} = \infty$ (2)	$\tau_{ij} = \infty$ AND $Z_i \equiv \bar{Z}$ (3)	RANDOMLY CHOOSE BRANCH LOCATIONS		
				2.5% (4)	Median (5)	97.5% (6)
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
B. Discrepancy between the Predicted and Actual Time of Branch Openings across Markets (years)						
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 1987–96 that are correctly predicted by different model variants. Panel B presents the discrepancy in the predicted and actual timing 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 $i \in C$). Columns 4–6 present the predictions of a model variant that randomly selects the locations of new branches, with col. 5 presenting the median prediction of 1,000,000 independent simulations and cols. 4 and 6 indicating the lower and upper bounds of the 95% confidence interval, respectively.

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, respectively, of the 95% confidence interval. 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 fig. OA.3 [app. 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 [app. 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 column 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.

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 1987–96 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.

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 (app. 3.7.6) report

⁴² We set this difference to 10 years for branches opened between 1987 and 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 ($1,428 - 406 - 431 = 591$).

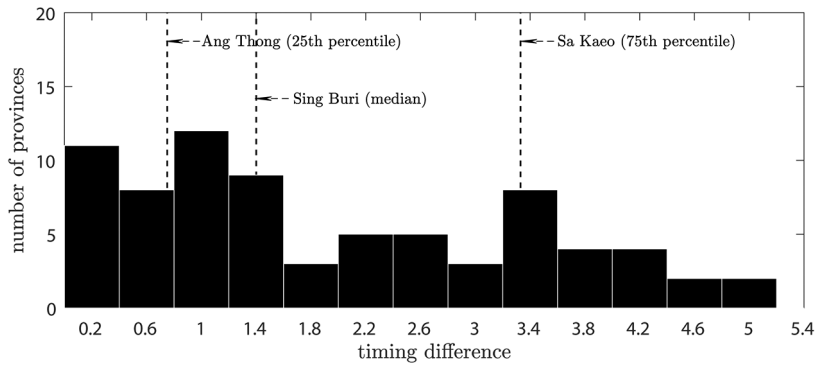


FIG. 7.—Distribution of province-level timing differences. The province-level timing difference is computed as the average discrepancy between the predicted and actual years of branch openings across markets within each province.

branch locations for every year in the 1986–96 period in the two provinces corresponding to the 25th and 75th percentiles, respectively, of the distribution of province-level average timing differences.

VI. 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 affects 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 $\xi_{i,t}$. 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 $\xi_{i,t}$ remains fixed at its 1986 value. Similarly, to isolate the deposit channel, we allow only $\xi_{i,t}$ 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.

⁴³ Although we focus on bank expansion, the model's dynamics are shaped by two forces: bank expansion and migration. In app. 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 app. 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.

A. 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, that is, 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 the locations of most branches (table 3) and matches the empirical estimates for the local effects of branch openings (fig. 5).

Figures 8A–8C show that, in general, the model-implied changes in occupational structure (solid lines) are consistent with those in the data (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

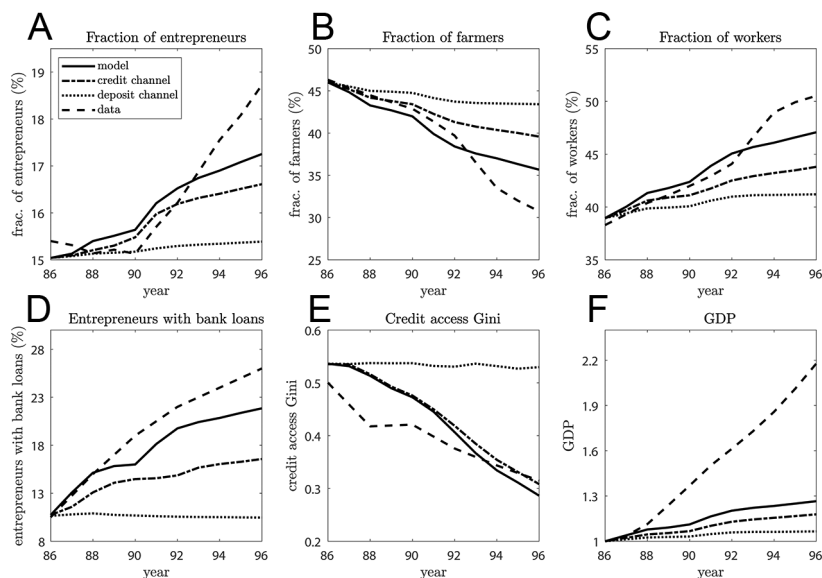


FIG. 8.—Aggregate dynamics, 1986–96. In the model, GDP is calculated according to equation (3.28) in appendix 3.6, in which we also provide a decomposition of GDP growth. The level of GDP in 1986 is normalized to 1. The data variables are constructed in appendix 1.3.

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

Figures 8*D* and 8*E* show that the model accounts well for the significant change in credit access conditions in the data. As shown in figure 8*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 figure 8*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 1986–96 period, compared with the data.

Finally, figure 8*F* 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 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 dash-dotted and 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 (fig. 8*A*) and the labor transition from farmers to workers (fig. 8*B*, 8*C*). Not surprisingly, the credit channel significantly affects the economy's credit access conditions (fig. 8*D*, 8*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 branch to expand the scale of their businesses, which boosts employment and output.

⁴⁴ A strong transition from agricultural to nonagricultural 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.

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

In figure 8F, 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 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 appendix 4.2.1 for clarification of the above channels using the model.

B. 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

⁴⁶ The 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 (fig. 8D), 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.

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.

1. Overall Change in Income Inequality across Households

Figure 9 illustrates the implications for income inequality across all households in the economy. In the data, figure 9A shows that the income Gini coefficient increases from 1986 to 1992 and decreases thereafter (dashed line, right-hand y-axis). This salient inverted-U shape is consistent with the Kuznets hypothesis. The Gini coefficient (hereafter “Gini”) does not capture the entire distribution of income, especially the higher-order moments and tail distributions (Güvenen et al. 2015, 2017). In figures 9B and 9C, 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 in figure 9A. By contrast, the share of the bottom 50% is U-shaped.

The solid lines in figure 9 plot the income inequality dynamics predicted by our model, based on the left-hand y-axis. Comparing the solid and 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 the data, the income Gini increases significantly from 1986 to 1992 and declines thereafter.

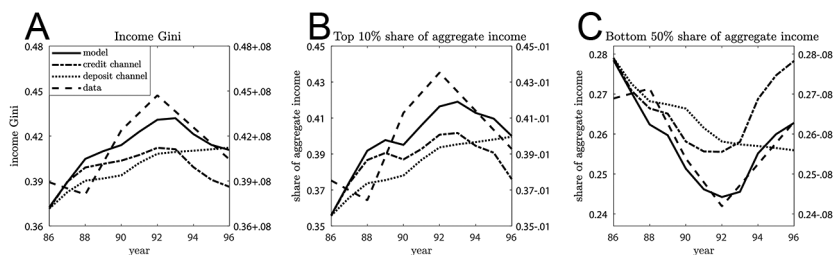


FIG. 9.—Overall income inequality across households, 1986–96. A, Income Gini coefficient across all households in the economy. We construct the income distribution of all households and compute aggregate income as the sum of all households’ income. B, C, Share of aggregate income earned by the top 10% and bottom 50% of the distribution, respectively. The left-hand y-axis is for the model (i.e., model, credit channel, and deposit channel), and the right-hand y-axis is for the data. The right- and left-hand y-axes differ by a constant, which represents the average level differences between the model (solid line) and the data (dashed line) for the 1986–96 period. The data variables are constructed in appendix 1.3.

The model sheds further light on the impact on the income Gini through the credit and deposit channels of bank expansion. In figure 9A, the credit channel (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 (dotted line), the income Gini increases persistently over the 1986–96 period. When both channels are active, the baseline model (solid line) implies a very pronounced inverted-U shape for the income Gini, as in the data.

The right- and left-hand 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 1986–96 period. It is evident that the average share of the top 10% (fig. 9B) in the model is very similar to that in the data, differing by only 1%. However, the average level of the income Gini (fig. 9A) is about 0.08 lower and that of the bottom 50% (fig. 9C) 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 De 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.

2. 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. Figure 10A plots the within-market income Gini, computed using the income distribution of households within the same markets. In both the data and the model, the within-market income Gini increases steadily between 1986 and 1996. Similar to figure 9A, because of 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 dash-dotted and dotted lines illustrate the respective 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

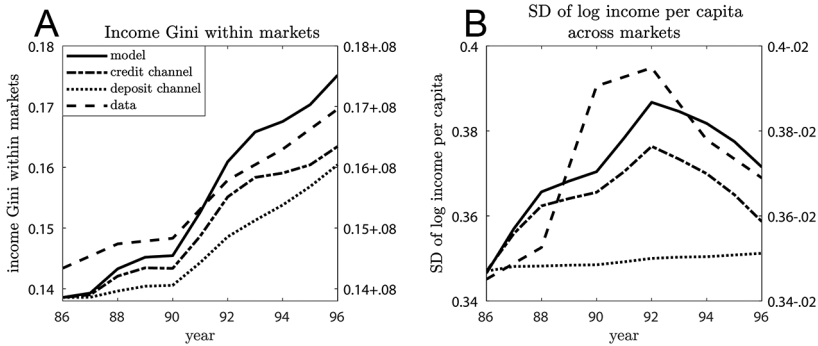


FIG. 10.—Income inequality within and across markets, 1986–96. For each market, we construct the income distribution of households and calculate the income Gini coefficient across these households. *A*, Average within-market income Gini coefficient across all markets in the economy. *B*, Standard deviation 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-hand y-axis is for the model (i.e., model, credit channel, and deposit channel), and the right-hand y-axis is for the data. The right- and left-hand y-axes differ by a constant, which represents the average level differences between the model (solid line) and data (dashed line) for the 1986–96 period. The data variables are constructed in appendix 1.3.

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.

Figure 10*B* 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 1986–92 period and declines thereafter (dashed line, right-hand y-axis), exhibiting an inverted-U shape similar to that of the overall income Gini in figure 9*A*.⁴⁷

By reproducing the inverted-U shape for cross-market income inequality (solid lines, left-hand y-axis in fig. 10*B*), 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,

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

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. This becomes evident if we decompose the impacts into the credit and deposit channels: the credit channel significantly boosts local income (see fig. 8*F*), generating a similar inverted-U shape (dash-dotted line), but the mild effect of the deposit channel is insufficient to generate this shape. Instead, as the dotted line in figure 10*B* 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 by only 0.02 (comparing the left- and right-hand y -axes in fig. 10*B*). 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 (app. 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.

C. Welfare Implications within and across Markets

Our model provides well-defined normative metrics to evaluate the welfare implications of bank expansion. For the 1986–96 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 sec. VI.A). Both channels have significant redistributive effects within and across markets, as discussed below.

1. Welfare within Markets

We first investigate welfare changes across households with different levels of total wealth $m_i + a_i$ and talent z_i . Figures 11*A*–11*C* focus on a market in which the branch opens in 1990 (i.e., no branch exists in 1986), with the

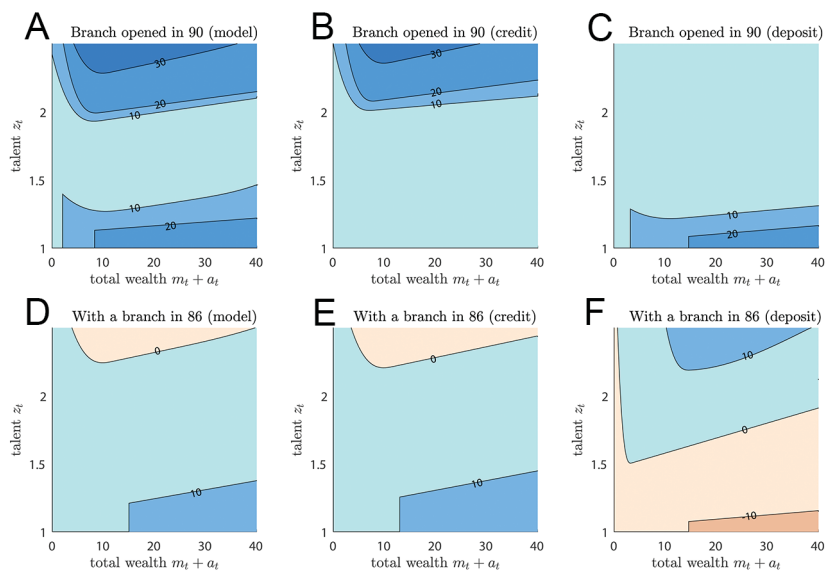


FIG. 11.—Welfare changes across households within the same markets, 1986–96: the consumption-equivalent welfare gains for the 1986–96 period for households of different total wealth $m_t + a_t$ and talent z_t are calculated (see app. 3.4). A–C focus on a market where no branch exists in 1986 and a branch is opened in 1990. The three panels present the implications of the baseline model, the credit channel, and the deposit channel, respectively. 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.

three panels representing the implications of the baseline model, the credit channel, and the deposit channel, respectively. It is evident that figure 11A displays a pattern similar to those of figures 11B and 11C combined, although the exact magnitudes of welfare gains differ slightly as a result of the interaction between the credit and deposit channels, which affects the equilibrium interest rate and wages. As shown in figure 11B, 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. Figure 11C 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 fig. 11A) 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 (fig. 10A) because these households already have higher income than other households.

Figures 11D–11F focus on a market that already has a branch in 1986. Figure 11D shows that households in this market have much smaller and even negative welfare gains, compared with those in figure 11A, 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.

Figure 11E 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 figure 11D. Thus, both the upper region enclosed by “0” and the lower-right region enclosed by “10” expand in figure 11E. Figure 11F focuses on the impact of the deposit channel. In this counterfactual experiment, new branch openings in other markets reduce only portfolio adjustment costs but not credit entry costs. The demand for deposits increases, resulting in a lower equilibrium interest rate—the general equilibrium effect flips the sign of the effect. Thus, the pattern displayed in *F* is the opposite of that in *E*: households in the upper region experience welfare gains, whereas those in the lower region experience welfare losses.

2. 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 nonmigrants 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 (app. 4.1).

Figure 12A focuses on the predictions of the baseline model. Different markets exhibit highly heterogeneous welfare changes. Markets that are initially far from branches but receive new branches during the 1987–96 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 1986–96 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.

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

VII. 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 nonfinancial assets over bank deposits. We consider a policy to mobilize rural deposits by subsidizing

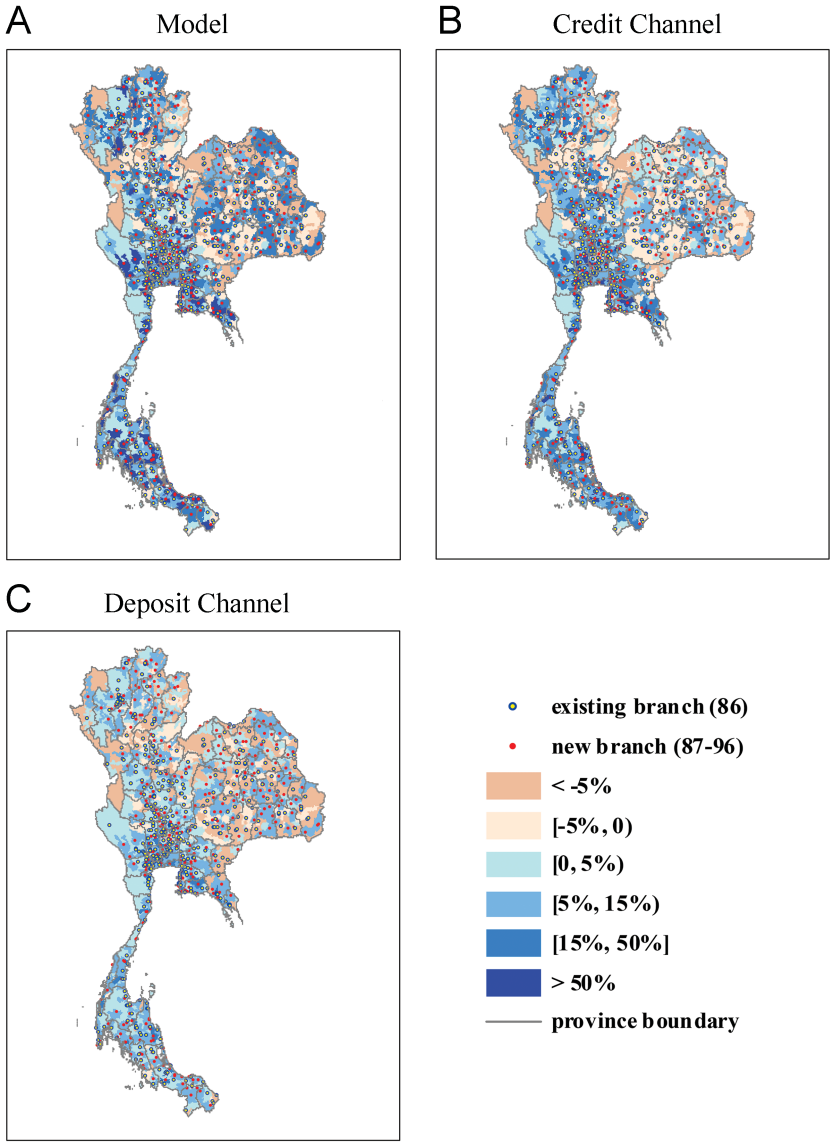


FIG. 12.—Market-level welfare changes, 1986–96: baseline model (A), credit channel (B), and deposit channel (C). Market-level welfare gains are household-level welfare gains weighted by the distribution of households.

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 $\zeta_{i,b}$ 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 (18) 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 policy makers' 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 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 1987–96 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. Figure 13A plots the fraction of new branches that open in distant markets (i.e., $d_{i,0} > \bar{d}$). Relative to the baseline model (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 (dash-dotted line). However, subsidizing household portfolio adjustment costs has little effect early on, and the effect becomes pronounced only in later years (dashed line). Intuitively, the portfolio adjustment cost subsidy provides incentives for households to hold more deposits, allowing them to accumulate wealth

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

⁴⁹ Because 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.

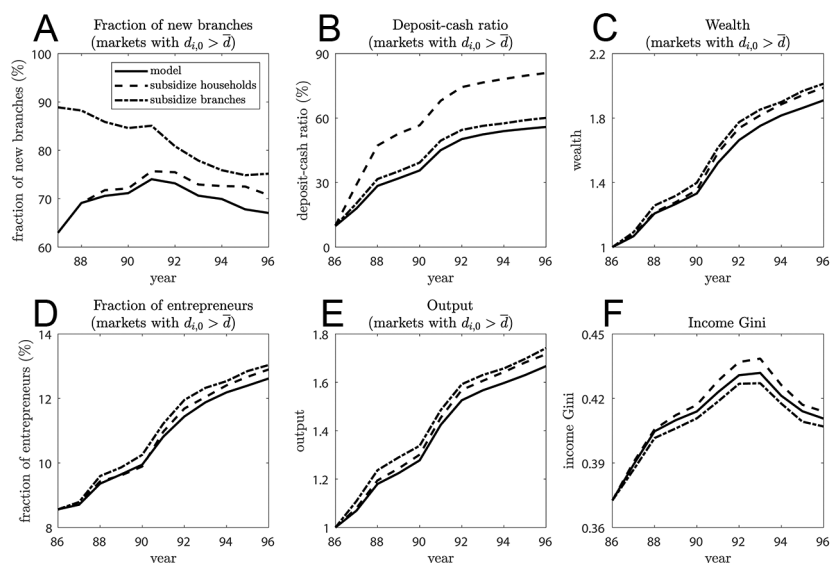


FIG. 13.—Impacts of financial sector policies. The dashed line represents the policy that subsidizes the portfolio adjustment costs of households in markets for which distance from the nearest branch in 1986, $d_{i,0}$, is greater than \bar{d} , the median distance from the nearest branch across all markets without branches in 1986. The dash-dotted line represents the policy that subsidizes new branches opened in markets with $d_{i,0} > \bar{d}$. A, Fraction of new branches opened since 1987 in markets where $d_{i,0} > \bar{d}$. B–E, Deposit-cash ratio, wealth (cash + deposits), fraction of entrepreneurs, and output, respectively, of markets with $d_{i,0} > \bar{d}$. F, Overall income Gini coefficient.

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.

Figures 13B and 13C support the above mechanism by illustrating the policies' impacts on the aggregate deposit-cash ratio and the wealth of distant markets, respectively. Subsidizing branches generates only a moderate increase in the deposit-cash ratio because of 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, figure 13C shows that subsidizing branches has a greater effect on wealth accumulation because it results in more new branch openings in distant markets (see fig. 13A) 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

Figures 13*D* and 13*E* show that both policies increase the fraction of entrepreneurs and output growth in distant markets, respectively. Again, the policy of subsidizing branches is more effective than that of subsidizing households. For example, for the study period, 1986–96, 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 a result, the output growth of markets close to existing branches in 1986 is lower under the two policies than it is in the baseline model.

Finally, figure 13*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 because of financial exclusion. As a result, cross-market income inequality falls, resulting in a lower overall income Gini than in the baseline model. By contrast, subsidizing households leads to higher overall income inequality than the baseline model. As discussed for figure 10*A*, 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 as a result of 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.

VIII. 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

⁵⁰ According 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 (Demirgüç-Kunt et al. 2018).

⁵¹ In 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 eq. (18). The average profits across the 431 new branches opened during the 1987–96 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.

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 1986–96 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 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.

Data Availability

Code replicating the tables and figures in this article can be found in Ji, Teng, and Townsend (2022) in the Harvard Dataverse, <https://dataverse.harvard.edu/dataset.xhtml?persistentId=doi:10.7910/DVN/UAJIRH>.

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