Branch Expansion versus Digital Banking: The Dynamics of Growth and Inequality in a Spatial Equilibrium Model

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Abstract

We develop a heterogeneous-agent model with local spatial markets to study the relationships among bank expansion, growth, and inequality. In the model, households choose their occupations, consumption, and holdings of loans and portfolio assets that vary by liquidity. Banks choose the locations of new branches, which affect the financial frictions facing households across regions. We calibrate the model using a geographic information system to evaluate the rapid bank expansion in Thailand between 1986-1996. The model quantifies the sources of growth and inequality over time and across space and the potential role of digital banking in substantially reducing regional heterogeneity.

1 Introduction

Implementing financial sector policies that promote growth is one of the key goals of developing economies. Most countries selectively target certain regions with an explicit emphasis on transitional dynamics, but their strategies differ. For example, financial reforms in Thailand from the 1980s to the 1990s focused on underdeveloped areas to improve financial inclusion. Reforms in China in the 1970s focused on advancing the capital market in the eastern coastal provinces; western inland areas were not prioritized until many years later. Many OECD countries focus on developing lagging regions to promote financial access and catch up (OECD, 2016). The US remains concerned about income and wealth inequality and equitable financial access in local markets (Furman, 2016; Nguyen, 2019).[1]

A growing number of papers emphasize the importance of spatial heterogeneity (Redding and Rossi-Hansberg, 2017). However, few studies address the connections between space, financial deepening, growth, TFP, and inequality during transitions. The objective of our paper is to provide a micro-founded macroeconomic framework for exploring the rich linkages across both space and time. We introduce local spatial markets in the context of a growth model featuring financial frictions (e.g., Greenwood, Sanchez and Wang, 2010; Buera and Shin, 2013; Midrigan and Xu, 2014). At the heart of our framework are financial frictions, captured by the cost of accessing financial accounts. We introduce ingredients which are novel in their combination. First, we model the costs of both credit access and portfolio adjustment for cash and deposits which differ in their liquidity, similar in spirit to the liquid and illiquid assets emphasized by Kaplan and Violante (2014).[2] Second, these costs differ across markets, depending on how close a market is to its nearest bank branch. New branches are opened endogenously by profit-maximizing banks. We use the model to predict and evaluate the impact of bank expansion in Thailand from 1986 to 1996, where we have detailed household survey data and geographic information system (GIS) data, which provide information on bank branch locations and road networks. The results shed light on the sources of growth and inequality over time and across regions. In a counterfactual experiment, we quantify what would have been the impact of digital banking in reducing regional heterogeneity.

Since the late 1980s, Thailand has adopted a series of financial liberalization policies, leading to the rapid expansion of banks' business operations. Panel A of Figure 1 shows that the number of regions with commercial bank branches steadily increased over the

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[1]The ConnectALL initiative launched in 2016 aimed to help Americans to access Internet and benefit from safe and affordable online payment, borrowing, and savings products. As of early 2019, a survey by Pew Research Center found that 26% of adults living in households earning less than $30,000 a year do not have broadband internet at home.

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

A. No. of markets with branches   B. Credit access ratio
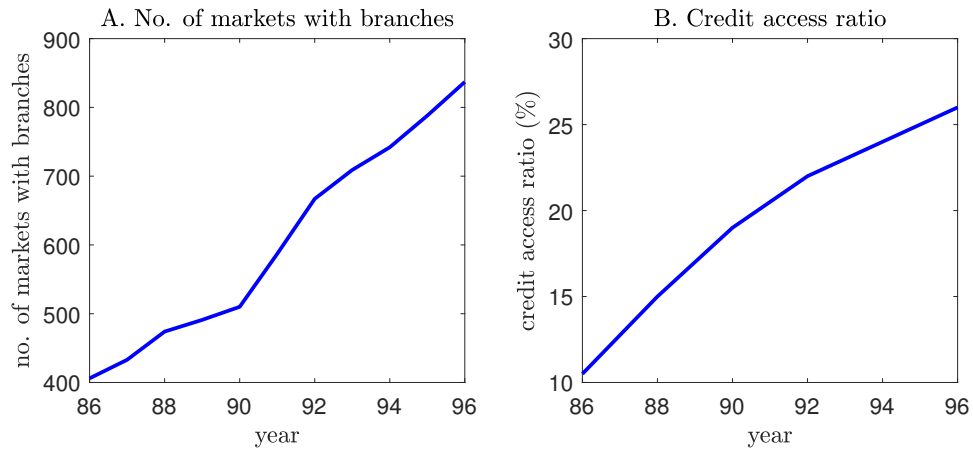
Note: Panel A plots the number of markets with at least one commercial bank branch, using data from the Bank of Thailand and various other financial institutions. Markets are defined in Section 2.2. Panel B plots the national credit access ratio, which is defined as the proportion of entrepreneurs with access to bank loans, as determined by the Thai Socio-Economic Survey.

Figure 1: Bank branches and credit access in Thailand, 1986-1996.

study period, more than doubling between 1986 and 1996. Many branches were opened in underdeveloped areas to improve financial inclusion. As a consequence, the national credit access ratio increased from about 10% in 1986 to more than 25% in 1996 (panel B of Figure 1). Moreover, bivariate local indicators of spatial association reveal significant spatial patterns. Regions with high concentrations of bank branches are associated with greater entrepreneurial activity and better credit access conditions (Felkner and Townsend, 2011).

These time-series and cross-sectional patterns motivate the development of a dynamic spatial equilibrium model to explore the rich linkages between bank expansion, various measures of financial deepening, and occupation choices over time and across space. In the model, we consider both heterogeneous markets and heterogeneous households within each market. Households optimally decide their occupations (i.e., farmer, worker, or entrepreneur), consumption, and holdings of assets (cash, bonds) and loans, and they face different financial frictions that depend on their distance from bank branches. Banks choose where to open new branches to maximize profits, taking into account the effects of branches in nearby regions and endogenous prices in general equilibrium. New branch openings lead to both lower credit entry costs and lower portfolio adjustment costs in immediate and nearby regions. Lower credit entry costs increase the proportion of households that choose to pursue entrepreneurship and households' demand for bank loans, capturing the credit provision channel of bank expansion. Lower portfolio adjustment costs increase households' demand for interest-bearing bonds (i.e., term deposits at banks), capturing the deposit mobilization channel of bank expansion.

These rich micro underpinnings allow our model to reproduce salient patterns in the data,

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even though those patterns are not targeted in our calibration. Specifically, the model correctly predicts more than 75% of the locations of new bank branches that opened between 1986 and 1996.[3] Moreover, the model can largely explain the transitional dynamics of various aggregate variables including GDP, TFP, credit access, the income Gini coefficient, and occupation. Further, the model predicts cross-regional patterns of bank locations, entrepreneurial activity, and credit access conditions that resemble those in the data. Finally, with a slight modification in some of the parameters, the model can predict remarkably well the decline in GDP associated with the 1997 financial crisis (Online Appendix 3.6), though that is not our main focus. The baseline prediction for the 1986-1996 period is also relatively insensitive to the inclusion of the 1996-2011 period (Online Appendix 3.5).

Through the lens of this model, we examine regional heterogeneity, traceing out the origins of growth and inequality and their trends over space. By decomposing GDP growth across regions, we show that Thailand's GDP growth is attributed to markets that were distant from bank branches in 1986. In particular, regions that received new branches experienced as much as 300% growth in local GDP and 100% growth in local TFP, leading to a welfare gain of over 270% from 1986 to 1996. By contrast, the local GDP, TFP, and welfare of regions that already had branches in 1986 changed little. We also find that bank expansion generates a large amount of spatial redistribution, which equalizes entrepreneurs' income but amplifies wage differences across regions. The higher cross-regional income inequality of workers is mainly caused by local wage takeoffs, which occur at different times across markets. This pattern is not produced by models without spatial heterogeneity.

The model reveals significant inter-regional capital flows within Thailand. In equilibrium, markets closer to bank branches have excess demand for bank loans relative to their local households' deposits. Capital flows into these markets through banks' branching networks, and the interest rate is set to clear the national capital market. The large endogenous flow of funds contributes to the high level of inequality among entrepreneurs in different regions by providing those living closer to branches with greater access to loans.

Using the calibrated model, we run counterfactual experiments to quantify the importance of providing credit versus the importance of mobilizing deposits. We quantify the deposit mobilization (credit provision) channel by assuming that new branch openings reduce only the portfolio adjustment (credit entry) costs in nearby regions, leaving the credit entry (portfolio adjustment) costs unchanged. We show that the credit provision channel alone generates a cumulative GDP growth of 66% during the decade, whereas the deposit mobilization channel alone generates a cumulative GDP growth of only 3%. However, despite its small quantitative impact, the deposit mobilization channel significantly amplifies the credit provision channel,

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[3] In our calibration, we choose branch setup costs to match the number of new branches in each year, and we predict where these branches will be opened.

due to the complementarity of these two channels.[4] We find that GDP increases by an additional 9% (75% − 66%) when the deposit mobilization channel is introduced on top of credit provision, as the baseline simulation with fully functioning new branches generates a cumulative GDP growth of 75%. Intuitively, the deposit mobilization channel increases the supply of funds as households put larger proportions of their wealth into banks. However, in the counterfactual scenario, where new branches reduce portfolio adjustment costs but not credit entry costs in nearby regions, the talented entrepreneurs living in these regions still cannot afford to pay for credit entry. As a result, the increased supply of funds is absorbed by entrepreneurs in other regions (those close to branches in 1986) who already have credit access and who are on average less talented. This results in capital misallocation and thus a small increase in GDP. By contrast, when new branch openings reduce both portfolio adjustment costs and credit entry costs, talented entrepreneurs who were previously excluded from the financial market in these regions can borrow because of the low credit entry costs, boosting GDP growth more significantly.

The regional difference is further illustrated by a final set of experiments in which we compare the model's baseline path with one in which digital banking is introduced in the initial year, 1986, which decreases deposit and credit costs to zero.[5] We show that digital banking greatly eliminates regional heterogeneity, although the effects on other dimensions are not instantaneous. As it takes time for households to accumulate wealth and savings, the immediate effects on GDP and TFP of introducing digital banking are much smaller than the long-run effects.

A further decomposition is used to gauge the impact of replacing some or all paper currency with interest-bearing accounts, as in some versions of central bank digital currency (CBDC) administered through the commercial banking system. More generally, digital payments and financial access are emphasized in China, Hong Kong, India, and Brazil, as leading examples. We lower deposit costs to zero in the initial year, while letting branch expansion lower credit costs, as in the baseline. This eliminates currency previously held for consumption smoothing, from household wealth portfolios. We compare this with the impact of lowering credit costs to zero in the initial year while letting branch expansion lower deposit costs, as in the baseline. This removes the use of currency by entrepreneurs who

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[4]The development economics literature shows that complementarity between inputs and constraints is important to the allocation of resources. For example, Hirschman (1958) emphasizes complementarity through linkages in a production network. Kremer (1993) and Blanchard and Kremer (1996) build models with complementarity among different tasks or chains of production. Jones (2011, 2013) focuses on complementarity among production inputs. Dabla-Norris et al. (2020) study complementarity among financial constraints.

[5]With the calibrated model in hand, we could also conduct less radical experiments, such as subsidizing but not eliminating branch entry costs, in designated rural areas for example. With our explicit bank optimization problem incorporated, one could then examine counterfactual branch placements and their impacts on the aggregate and market economies.

self-finance the purchase of capital. Our comprehensive digital banking experiments clarify the contribution of each piece and the complementarity between the two.

Related Literature. Our model contributes to the macro-development literature that applies micro-founded general equilibrium models to study growth, inequality, and entrepreneurship.[6] Our paper is closest to works focusing on the nexus between financial development and growth (e.g., Greenwood and Jovanovic, 1990; Greenwood, Sanchez and Wang, 2010, 2013; Buera and Shin, 2013; Midrigan and Xu, 2014; Moll, 2014). Motivated by the theoretical work of Greenwood and Jovanovic (1990), we emphasize the cost of accessing financial accounts, which can be naturally mapped onto the market's distance from bank branches. A key difference between our approach and existing models is that we explicitly model local spatial markets, based on which dynamic bank expansion is evaluated.[7] Although similar aggregate dynamics can be generated in a one-market model, a realistic evaluation of dynamic bank expansion (and its channels) that can be used for welfare analysis, including counterfactuals, requires a spatial equilibrium model that incorporates multiple local markets. Our model can reproduce the interesting regional heterogeneity in entrepreneurship and credit access seen in the data, as well as the flow of funds and local wage takeoffs across regions.

Modeling portfolio adjustment costs dates back at least to Baumol (1952), Tobin (1956), and Miller and Orr (1966). 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 and conduct an

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[6]See, e.g., Banerjee and Newman (1993); Lloyd-Ellis and Bernhardt (2000); Quadrini (2000); Gine and Townsend (2004); Cagetti and Nardi (2006); Townsend and Ueda (2006); Jeong and Townsend (2008); Amaral and Quintin (2010); Buera, Kaboski and Shin (2011); Felkner and Townsend (2011); Kaboski and Townsend (2011); Moll (2014); Cheremukhin et al. (2015, 2017); Moll, Townsend and Zhorin (2017); Dabla-Norris et al. (2020). 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; Banerjee et al., 2015; Augsburg et al., 2015). Recently, Bergquist et al. (2020) combine field experiments and structural models to shed light on the general equilibrium effects of policy intervention at the national level.

[7]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), but to our knowledge, there is no formal dynamic spatial-based model of the impact of dynamic bank expansion.

experiment that introduces digital currency, which replaces branch banking. Other studies emphasize heterogeneity in the effects of monetary policy (Doepke and Schneider, 2006; Auclert, 2019). However, 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 though commercial banks, as we do, but for us savers and borrowers are endogenously determined. Aguirregabiria, Clark and Wang (2016) examine the cross-state expansion of bank branches subsequent to the Riegle-Neal Act. Corbae and D'Erasmo (2019) 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.[8] Our paper is closest to Desmet and Rossi-Hansberg (2014), as we develop a dynamic model of growth with an explicit emphasis on geography and locations. However, our paper differs from theirs in several respects. First, our focus is on economic growth during transitions triggered by bank expansion, 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.[9] Modeling heterogeneous agents in each market allows us to better connect our theory with household data, allowing us to capture the rich interaction between inequality, 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.[10]

The rest of the paper is organized as follows. We introduce the spatial data and define the markets in Section 2. The model is described in Section 3, calibrated in Section 4, and validated against the data in Section 5. In Section 6, we evaluate the model's implications regarding the sources of growth and inequality, flow of funds, and underlying channels. In

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

[9]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 inter-regional trade.

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

Section 7, we shed light on issues related to digital banking. Finally, Section 8 concludes.

2 Spatial Data, GIS, and Markets

Thailand's economy motivates the development of our spatial equilibrium model of dynamic bank expansion. Since the late 1980s, Thailand has implemented a series of financial liberalization policies (Abiad, Oomes and Ueda, 2008). We focus on the decade from 1986 to 1996, during which the Thai economy underwent swift economic expansion marked by uneven financial deepening and the rapid expansion of commercial bank branches.[11] 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; we hope to extend the analysis to other countries.

2.1 Data

Our GIS data contain high-resolution spatial data on bank locations, digitized major and minor road networks, and political boundaries at various administrative levels. We obtain our GIS data from the Thailand Environment Institute. These data provide detailed information on 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 of road. We estimate the average vehicle speed for each type of road based on real-time information and obtain the car travel time for every road segment (see Online Appendix 1.2).[12] Commercial bank branch locations in each year are constructed using data from the Bank of Thailand. Branch locations are mapped directly onto the GIS data for Thailand according to the location of the nearest village or the nearest major road intersection.

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[11]We do not analyze the 1997 crisis. Instead, we focus on the prior growth period to understand the endogenous linkages between financial deepening, growth, and inequality across regions. In Online Appendix 3.6, we show that the model-implied transitional dynamics between 1986-1996 would be virtually unchanged even if households fully anticipated the 1997 financial crisis.

[12]Our paper focuses on the expansion of commercial bank branches, which are the central players in the Thai financial system. They jointly absorbed 80.9% of deposits and accounted for 73.1% of total financial system assets during the study period. We do not consider branches of the Bank for Agriculture and Agricultural Cooperatives, a state-owned enterprise.
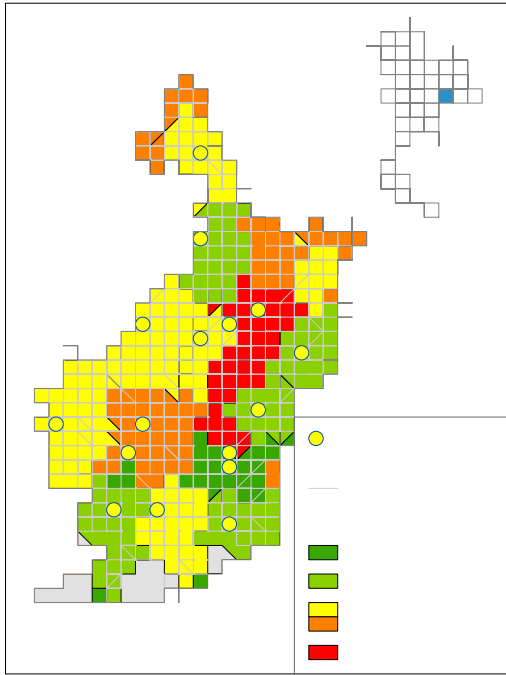
A. Local spatial markets in the GIS data   B. Mapping to the model
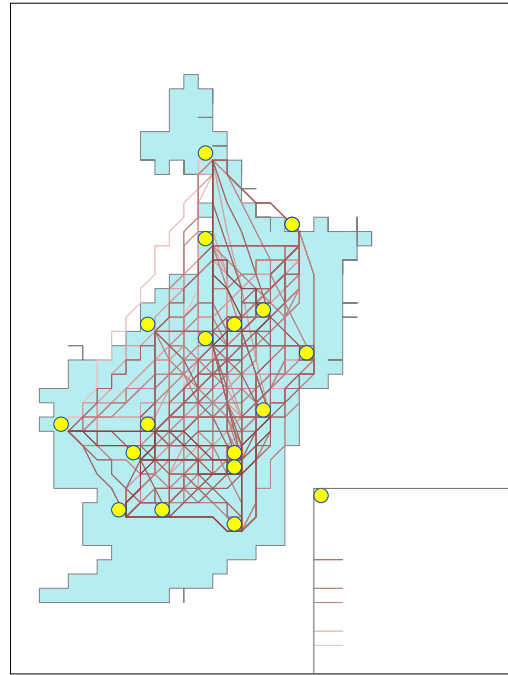
Note: Panel A plots the local spatial markets in the GIS data for Buriram province in Thailand. The yellow nodes represent commercial bank branch locations, and the small gray dots represent villages. The thick gray lines represent the borders of each market, and the thin gray lines represent the road network. The different colors of the markets indicate their population densities. Panel B plots the model economy of Buriram province. The yellow nodes correspond to the local spatial markets that enclose the branch locations in panel A. These markets are connected by links, and the distance between each pair of markets is measured by car travel time along the actual road network, which is shown in panel A.

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

2.2 Local Spatial Markets

In Thailand, commercial bank branches are generally opened in populous regions in which households engage in market activity. We have actual branch locations in the data, which are represented by their latitudes and longitudes. Although our study period for model evaluation is from 1986 to 1996, our definition of markets is based on actual commercial bank branch locations in 2011, the latest year of data available to us. In total, we identify 1,428 branch locations, based on which we define local markets, which we use as actual and potential branch locations in the study period. Each market includes only a single branch location, and the borders that separate markets are determined by the travel times along the road network. Any village or point on road within a market has a minimum travel time to the branch location in the market, which is less than the travel time to the branch locations in other adjacent markets. The population of each market is estimated as the sum of the village

and municipal populations in 1986.[13] The population density within a market is equal to the market's population divided by the market's area computed from GIS data.

As an illustration, Figure 2 plots the local spatial markets in the GIS data for one province and how they map onto our model, which is developed in Section 3. In panel A, the large yellow nodes represent the commercial bank branch locations in 2011. In a given year between 1986 and 1996, some of these locations may or may not have branches in the data. The gray 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. In our model, we ignore the travel time within a market for tractability, which is equivalent to assuming that households from different villages (small gray dots) within a market are all located at the branch location enclosed in the market. Panel B presents our model economy which consists of the local spatial markets corresponding to the branch locations in panel A. These markets are connected via road links, forming a network. The distance between each pair of markets is measured by the car travel time between the branch locations in the two markets along the road network. The other economic variables are constructed from household and village surveys (see Online Appendix 1.1).

3 Model

We develop a spatial equilibrium model to quantitatively evaluate the impact of dynamic bank expansion through different channels, over time, and across space.

3.1 Basic Environment

Time is discrete and is indexed by t. The economy consists of N markets, indexed by $i = 1, ..., N$, representing different geographical regions. In each market i, there is a continuum of heterogeneous households of measure Π_i, capturing market size. We do not allow households to migrate, so the size of each market is fixed at Π_i. 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, with $\tau_{ij} \equiv 0$ for $i = j$. The market size and road network are exogenously specified and do not change over time.

Although the place of residence and road network are exogenous, the financial intermediation network evolves endogenously over time. Markets differ in their access to finance: some

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[13]The population of each village is mapped onto its nearest market based on the road network, and the population of each municipality is likewise assigned to the markets within its administrative boundary.

markets have bank branches, while others do not. Households in markets with bank branches can obtain financial services (i.e., take out loans or invest in bonds) locally, whereas those in markets without branches must travel to nearby markets to borrow and lend. 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 capacity, i.e., $\Pi_i < h$.[14]

We use the binary indicator $B_{i,t}$ to show whether market i has a branch at time t ($B_{i,t} = 1$) or not ($B_{i,t} = 0$). Denote by Φ_t the set of markets with bank branches at time t, i.e., $B_{i,t} = 1$ for all $i \in \Phi_t$. We define the distance from the nearest bank branch for households in market i at time t as follows

$$v_{i,t} = \min \left\{ \tau_{ij} : j \in \Phi_t, \Pi_j < h \right\}. \tag{3.1}$$

The variable $v_{i,t}$ depends on the branch distribution Φ_t, which is endogenously determined by banks' expansion strategy. In our model, the distance from the nearest bank branch $v_{i,t}$ fully captures the degree of financial frictions in market i.

3.2 Households

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

The wealth of households consists of cash-in-hand m_t and deposits a_t as a claim on the bonds acquired by banks in lending to firms. Both assets are denominated in consumption units. Households can purchase consumption goods c_t or capital k_t using cash m_t, but they cannot use bonds a_t to do so.[15] The tradeoff between the two savings instruments is that cash earns a zero return, while bonds earn the interest rate $r_t > 0$ in equilibrium. Transforming cash

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[14]For tractability, we do not consider rationing and we make the following assumptions. When $\Pi_i \geq h$, market i's households can always obtain financial services locally with probability one. When $\Pi_i < h$, households traveling to market i from other markets can always obtain financial services with probability one.

[15]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 linkages in goods markets. Even in the same geographical 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 the product markets (Menzio and Trachter, 2015; Kaplan and Menzio, 2016; Menzio and Trachter, 2018).

into bonds or vice versa requires households to pay the market-specific portfolio adjustment cost $\zeta_{i,t}$ of going to the bank.[16] The tradeoff between cash m_t and bonds a_t emphasized here is highly reminiscent of the main insight of optimal cash management models (Baumol, 1952; Tobin, 1956; Miller and Orr, 1966). A lower $\zeta_{i,t}$ motivates households to put more of their wealth into bonds. Motivated by the empirical evidence that the density of bank branches affects access to savings accounts (Célerier and Matray, 2019), we specify that $\zeta_{i,t} \equiv \zeta(v_{i,t})$ is strictly increasing in $v_{i,t}$, meaning that households travel to their nearest bank branch to obtain financial services and that the costs increase with distance. Modeling distance-dependent portfolio adjustment costs enables us to incorporate the effect of bank expansion on aggregate savings.[17] In Online Appendix 2.2, we show how the average deposit-cash ratio (a_t/m_t) varies with $v_{i,t}$ under our calibration.

Our modeling approach of the two assets m_t and a_t is similar in spirit to that of Kaplan and Violante (2014).[18] Bonds are liquid in the U.S. but not in developing countries. Adjustments between cash and bonds can only be made once per period. Thus, investing in bonds a_t is similar to making a term deposit, which is less liquid than holding cash. Moreover, 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.

Preferences. Households derive utility from consumption c_t and have preferences

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

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

Occupation Choice and Technology. In any period t, households can choose from three occupations: farmer, worker, or entrepreneur. Farmers earn a subsistence income f, which is exogenous and the same across markets. Workers supply one unit of labor inelastically and

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[16] 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.

[17] 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).

[18] Such two-asset models have been commonly adopted in recent macroeconomic models (e.g., Kaplan, Moll and Violante, 2018; Heathcote and Perri, 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, 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).

earn the endogenous market-specific wage $w_{i,t}$. Entrepreneurs operate a technology that uses capital k_t and labor l_t to produce output $q(k_t, l_t, z_t)$,

$$q(k_t, l_t, z_t) = z_t (k_t^\alpha l_t^{1-\alpha})^{1-\nu}, \tag{3.3}$$

where output increases with households' talent z_t. The parameter ν determines the span of control, and $1 - \nu$ represents the share of output accruing to variable factors. A fraction α out of this output goes to capital and $1 - \alpha$ goes to labor. Capital depreciates at rate δ. In each market i, the equilibrium wage $w_{i,t}$ is determined to clear the local labor market. The cross-market difference in the degree of financial frictions endogenously drives the differences in wage, entrepreneurship, and output.

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 deposit interest rate r_t by a margin χ, which determines the profits of financial intermediation that accrue to banks after subtracting the real intermediation costs.

There is limited participation in the credit market. To obtain a loan, entrepreneurs need to pay an upfront market-specific credit entry cost $\psi_{i,t} \equiv \psi(v_{i,t})$ using cash m_t, as in Greenwood and Jovanovic (1990). A lower $\psi_{i,t}$ motivates more entrepreneurs to borrow loans, increasing credit access. Motivated by the empirical evidence that road distance affects credit access (Agarwal, Mukherjee and Naaraayanan, 2019; Nguyen, 2019), we specify that $\psi(v_{i,t})$ is strictly increasing in $v_{i,t}$. The amount of capital used in production is subject to a borrowing constraint:[19]

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

The parameter $\xi \in [0,1]$ determines the tightness of borrowing constraints, with $\xi = 1$ representing autarky, where capital must be self-financed by entrepreneurs.

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[19] A micro foundation can be offered as 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 bonds 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 the collateral, $k_t + a_t$. We assume that the liquidation value of capital is uncertain at the time of contracting. With probability $1 - \xi$ the bank recovers the full value k_t, but with probability ξ the bank recovers nothing. Thus to avoid default, the amount of 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 capital constraint (3.4).
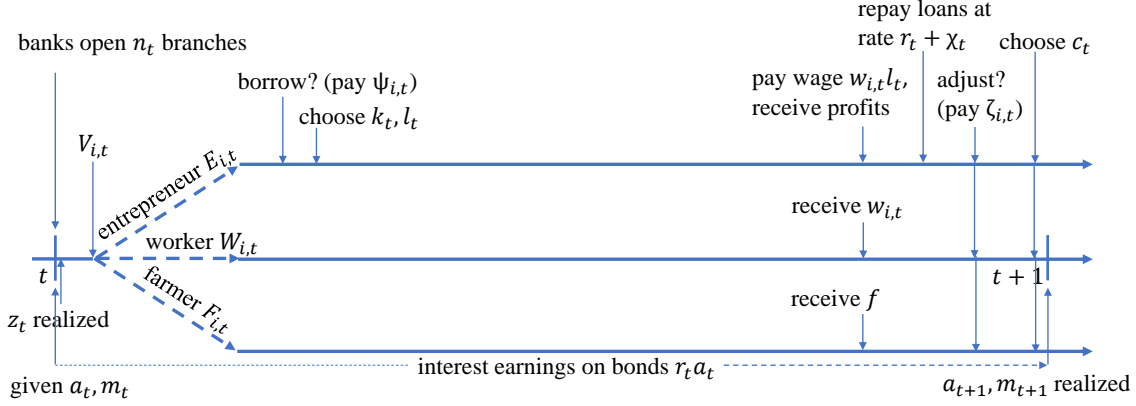
Figure 3: Timing of events.

Household Problem. The timing of decisions is presented in Figure 3. At the beginning of the period, new branches are opened, and the current talent z_t is realized, after which households make their occupation choice. Households 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). Finally, households decide whether to adjust their bond holdings and then choose their consumption. For further clarity, we present households' cash flow statements in Online Appendix 2.8.

We formulate households' problem recursively. Let $s_t \equiv \{z_t, m_t, a_t\}$ represent households' individual states. Denote by $V_{i,t}(s_t)$ the value function of a household in market i at the beginning of period t, before making the occupation choice. The value function depends on time t because we focus on transitional dynamics and households fully anticipate changes in the costs $\psi_{i,t}$ and $\zeta_{i,t}$ due to future branch openings. Denote by $F_{i,t}(s_t)$, $W_{i,t}(s_t)$, and $E_{i,t}(s_t)$ the household's value if she chooses to be a farmer, a worker, or an entrepreneur, respectively, at time t. The occupation choice is made to maximize utility,

$$V_{i,t}(s_t) = \max \left\{ F_{i,t}(s_t), W_{i,t}(s_t), E_{i,t}(s_t) \right\}. \tag{3.5}$$

The farmer's value is $F_{i,t}(s_t) = \max\{F_{i,t}^0(s_t), F_{i,t}^1(s_t)\}$, where $F_{i,t}^0(s_t)$ and $F_{i,t}^1(s_t)$ are respectively, the value conditional on not adjusting and adjusting the portfolio, given by

$$F_{i,t}^0(s_t) = \max_{c_t, m_{t+1}} \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_t \left[V_{i,t+1}(s_{t+1}) \right], \tag{3.6}$$

$$\text{s.t. } m_{t+1} + c_t = m_t + f,$$

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

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where cash m_t earns a zero return and bonds a_t earn the return r_t.

$$F_{i,t}^1(s_t) = \max_{c_t, m_{t+1}, a_{t+1}} \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_t \left[V_{i,t+1}(s_{t+1}) \right], \tag{3.7}$$

$$\text{s.t. } m_{t+1} + a_{t+1} + c_t = m_t + (1+r_t)a_t - \zeta_{i,t} + f, \text{ with } m_{t+1}, a_{t+1} \geq 0.$$

The worker's value is determined by solving a problem similar to the farmer's (i.e., equations (3.6) and (3.7)), except that the subsistence income f is replaced with the equilibrium local wage $w_{i,t}$ in market i. We present the workers' problem in Online Appendix 2.1. In equilibrium, it must be the case that $w_{i,t} \geq f$; otherwise, the local labor market in market i does not clear because households strictly prefer to be farmers rather than workers, resulting in a zero supply of labor. Further, if $w_{i,t} > f$, households strictly prefer to be workers, and farmers do not exist in market i. If $w_{i,t} = f$, households are indifferent as to whether they are workers or farmers. As a result, the supply of labor in market i is entirely determined by local entrepreneurs' demand for workers, and the remaining households not hired by entrepreneurs are farmers. Intuitively, this happens when market i is far away from bank branches, as 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 f. By reducing the credit entry cost $\psi_{i,t}$, bank expansion can generate local wage takeoffs across markets, increasing the cross-market income inequality among workers (see Section 6.1).

Finally, the entrepreneur's value function is

$$E_{i,t}(s_t) = \max\{E_{i,t}^{00}(s_t), E_{i,t}^{10}(s_t), E_{i,t}^{01}(s_t), E_{i,t}^{11}(s_t)\}, \tag{3.8}$$

where the first superscript denotes whether the entrepreneur adjusts (1) or does not adjust (0) the portfolio, and the second superscript denotes whether the entrepreneur borrows (1) or does not borrow (0). These values are determined recursively as follows. If the entrepreneur does not adjust the portfolio or borrow, her value is $E_{i,t}^{00}(s_t)$,

$$E_{i,t}^{00}(s_t) = \max_{c_t, k_t, l_t, m_{t+1}} \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_t \left[V_{i,t+1}(s_{t+1}) \right], \tag{3.9}$$

$$\text{s.t. } m_{t+1} + c_t = m_t - k_t + z_t(k_t^\alpha l_t^{1-\alpha})^{1-\nu} + (1-\delta)k_t - w_{i,t}l_t,$$

$$k_t \leq m_t,$$

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

The budget constraint implies that the entrepreneur uses cash m_t to buy capital k_t, and

the remaining $m_t - k_t$ earns a zero return. Profits are given by output $z_t(k_t^\alpha l_t^{1-\alpha})^{1-\nu}$ plus undepreciated capital $(1-\delta)k_t$ minus wage payments to workers $w_{i,t}l_t$.

If the entrepreneur adjusts and borrows (which requires $m_t \geq \psi_{i,t}$), her value is $E_{i,t}^{11}(s_t)$,

$$E_{i,t}^{11}(s_t) = \max_{c_t,k_t,l_t,m_{t+1},a_{t+1}} \frac{c_t^{1-\sigma}}{1-\sigma} + \beta \mathbb{E}_t\left[V_{i,t+1}(s_{t+1})\right], \tag{3.10}$$

$$\text{s.t. } m_{t+1} + a_{t+1} + c_t = -\left[1 + (r_t + \chi)\mathbb{1}_{\{k_t \geq m_t - \psi_{i,t}\}}\right]\left[k_t - (m_t - \psi_{i,t})\right] + (1 + r_t)a_t$$

$$- \zeta_{i,t} + z_t(k_t^\alpha l_t^{1-\alpha})^{1-\nu} + (1-\delta)k_t - w_{i,t}l_t,$$

$$k_t \leq (m_t + a_t - \psi_{i,t})/\xi, \text{ with } m_{t+1}, a_{t+1} \geq 0,$$

where $\mathbb{1}_{\{k_t \geq m_t - \psi_{i,t}\}}$ is the indicator function that equals one if $k_t \geq m_t - \psi_{i,t}$. This means that if the entrepreneur uses more capital k_t than her cash $m_t - \psi_{i,t}$, the difference is borrowed from the bank at the lending rate $r_t + \chi$. The other two cases $E_{i,t}^{10}(s_t)$ and $E_{i,t}^{01}(s_t)$ can be formulated similarly and are relegated to Online Appendix 2.1.

3.3 Banks

Competitive banks operate branches that are located in different markets of the economy. A branch makes profit by channeling funds from households to entrepreneurs. The per-unit cost of funds is the interest rate r_t, which is offered to households for their deposits. The revenue per unit of loans is the lending rate r_t^l. Thus the net profit per unit of funds is $r_t^l - r_t = \chi$. Consider market i with a branch at time t ($B_{i,t} = 1$). The present value of the profits that the branch receives for $t' \geq t$ is given by[20]

$$\Theta_{i,t} = \chi \sum_{t'=t}^{\infty} \beta^{t'-t}\left[D_{i,t'} + \sum_{j \in \left\{j:v_{j,t'}=\tau_{ij},B_{j,t'}=0\right\}} D_{j,t'}\right]. \tag{3.11}$$

In equation (3.11), the total deposits that the branch in market i receives from households include two parts. The term $D_{i,t'}$ captures the deposits of households in market i at time t', defined in equation (3.17) below. The term $\sum_{j \in \left\{j:v_{j,t'}=\tau_{ij},B_{j,t'}=0\right\}} D_{j,t'}$ captures the deposits of households in other markets that travel to market i to make deposits. These markets are identified by the set $\left\{j:v_{j,t'} = \tau_{ij}, B_{j,t'} = 0\right\}$, meaning that they do not have a local bank branch ($B_{j,t'} = 0$) and that their distance from the nearest bank branch at time t', $v_{j,t'}$, is equal to the distance between market i and market j. The markets included in the set

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[20]In equilibrium, the economy-wide capital market clearing condition ensures that all deposits in equation (3.11) are lent out to entrepreneurs and generate profits at rate χ.

$\left\{ j : v_{j,t'} = \tau_{ij}, B_{j,t'} = 0 \right\}$ evolve endogenously as new branches are opened over time.

Bank branch expansion is determined by a free entry condition. In period t, banks can set up a new branch at a cost ω_t in markets without branches. For tractability, we assume that banks do not know ex ante in which market they will end up with a branch.[21] Suppose that the total number of branches opened in period t is $n_t \geq 0$. At the beginning of period t, these branch locations are optimally chosen to maximize the total profits $\Theta_t(n_t)$ from n_t newly opened branches. The n_t locations will then be randomly assigned to the banks that have expressed the intention to set up new branches and that have paid the cost ω_t. The total profits $\Theta_t(n_t)$ are given by

$$\Theta_t(n_t) = \max_{\Phi_t^{new}} \sum_{i \in \Phi_t^{new}} \Theta_{i,t}, \tag{3.12}$$

$$\text{s.t.} \quad B_{i,t-1} = 0 \quad \text{for all} \ \ i \in \Phi_t^{new}, \tag{3.13}$$

$$|\Phi_t^{new}| = n_t. \tag{3.14}$$

Thus, given n_t, the optimal location choice for new branches boils down to solving a combinatorial programming problem (3.12), in which the set of new branches Φ_t^{new} opened in period t is chosen optimally, subject to two constraints. Constraint (3.13) indicates that new branches are opened in markets without branches in period $t-1$. Constraint (3.14) indicates that the number of new branches is given by n_t, where the symbol $|\cdot|$ denotes the cardinality of a set.

For the banks that have paid the setup cost ω_t, the expected profits of opening one branch are $\Theta_t(n_t)/n_t$ because banks are assigned randomly to the markets in set Φ_t^{new}. The total profits $\Theta_t(n_t)$ have decreasing returns to scale because the most profitable markets will be chosen first when solving problem (3.12). As a result, the expected profits of a branch $\Theta_t(n_t)/n_t$ are decreasing in n_t; the free entry condition ensures that in equilibrium,

$$\frac{\Theta_t(n_t + 1)}{n_t + 1} < \omega_t \leq \frac{\Theta_t(n_t)}{n_t}. \tag{3.15}$$

The location choice problem (3.12) is forward looking because $\Theta_{i,t}$ includes profits made by the branch in the future, internalizing the possibility that new branches will be opened in subsequent periods. Intuitively, because households can travel to other markets along the road network to obtain financial services, future branches that are opened in nearby markets can

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[21]It is as if banks apply for permits to open a branch but regulators determine where. If we allow banks to freely choose locations ex ante, they may strategically move first even within each period due to the preemption incentive, which makes the model intractable. Our assumption essentially implies that all banks make simultaneous entry decisions within the period, similar to Jia (2008). In our dynamic model, however, different from the static setting of Jia (2008), banks that open branches in period t internalize the impact of future branch openings on their profits.

potentially reduce the profits of existing branches (by changing the term $\sum_{j\in\{j:v_{j,t}=\tau_{ij},B_{j,t}=0\}} D_{j,t}$ in equation (3.11)). Moreover, the location choice problem (3.12) internalizes the impact of new branches on $\Theta_{i,t}$ through the endogenous interest rate r_t and wages $w_{i,t}$. In other words, the choice of branch locations that we solve is consistent with a rational expectation equilibrium.

Because of the interaction effects through network linkages, the combinatorial programming problem (3.12) is NP-hard, and impossible to solve exactly given the large number of markets that we consider in our calibration. Therefore, we propose a tractable numerical algorithm that solves the problem approximately in polynomial time (see Online Appendix 4). In a nutshell, we break banks' branch-opening problem over the whole country into a set of smaller problems that focus on specific segments of the country. These segments are constructed using the *k*-medoids clustering algorithm in machine learning to ensure that there is little interaction among locations in 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 of the segments' location choices and transforming the problem into a tractable multiple-choice knapsack problem.

3.4 Equilibrium and Aggregation

Figure 4 presents the circular flow of our model to facilitate discussion of equilibrium. Denote by $\Psi_{i,t}(s)$ the cumulative distribution function (CDF) of households of type $s = \{z, m, a\}$ in market i and period t. Given the initial distribution $\Psi_{i,0}(s)$ for all $i = 1, ..., N$ at $t = 0$, and the cost of opening branches ω_t for $t \geq 0$, the competitive equilibrium consists of allocations of new bank branches Φ_t^{new}, consumption $c_{i,t}(s)$, savings in the form of cash $m_{i,t+1}(s)$ and bonds $a_{i,t+1}(s)$, occupations, credit access, portfolio adjustments, capital $k_{i,t}(s)$, and labor $l_{i,t}(s)$ for each type s, sequences of the joint distribution $\Psi_{i,t}(s)$ of talent, cash, and bonds, prices $w_{i,t}$, and r_t for each market i and $t \geq 0$, such that the following conditions are satisfied.

i). Given $\{\Phi_\tau, r_\tau\}_{\tau=0}^\infty$ and $\{w_{i,\tau}\}_{\tau=0}^\infty$ for $i = 1, ..., N$, households of type s in each market i choose $c_{i,t}(s)$, $a_{i,t+1}(s)$, $m_{i,t+1}(s)$, occupations, credit access, portfolio adjustments, $k_{i,t}(s)$, and $l_{i,t}(s)$ optimally by solving problems (3.5) to (3.10) for all $t \geq 0$.

ii). Given the allocation of households' variables, distribution $\{\Psi_{i,\tau}\}_{\tau=0}^\infty$, prices $\{r_\tau\}_{\tau=0}^\infty$, and $\{w_{i,\tau}\}_{\tau=0}^\infty$ in each market i, the allocation of new bank branches Φ_t^{new} solves problem (3.12), where the number of new branches n_t satisfies (3.15).

iii). The equilibrium interest rate r_t is determined by the economy-wide bond-market clearing condition in period t:

$$\sum_{i=1}^N D_{i,t} = \sum_{i=1}^N \left[\Pi_i \int [k_{i,t}(s) - (m - \psi_{i,t})] \, \mathbb{1}_{\{k_{i,t}(s) \geq m - \psi_{i,t}\}} \mathrm{d}\Psi_{i,t}(s) \right], \tag{3.16}$$

A. Circular flow of the aggregate economy
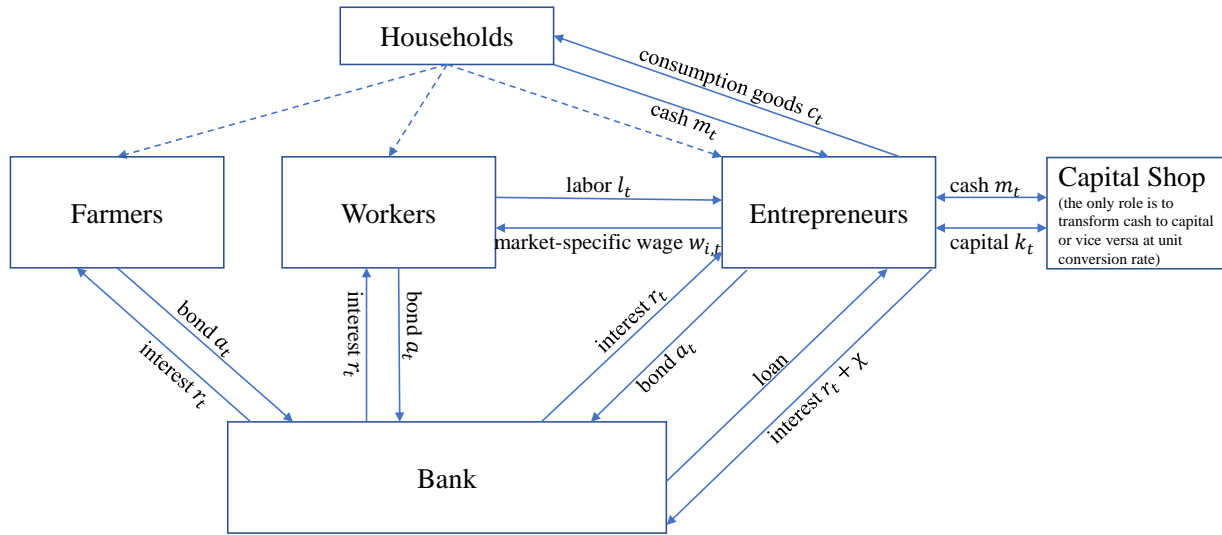
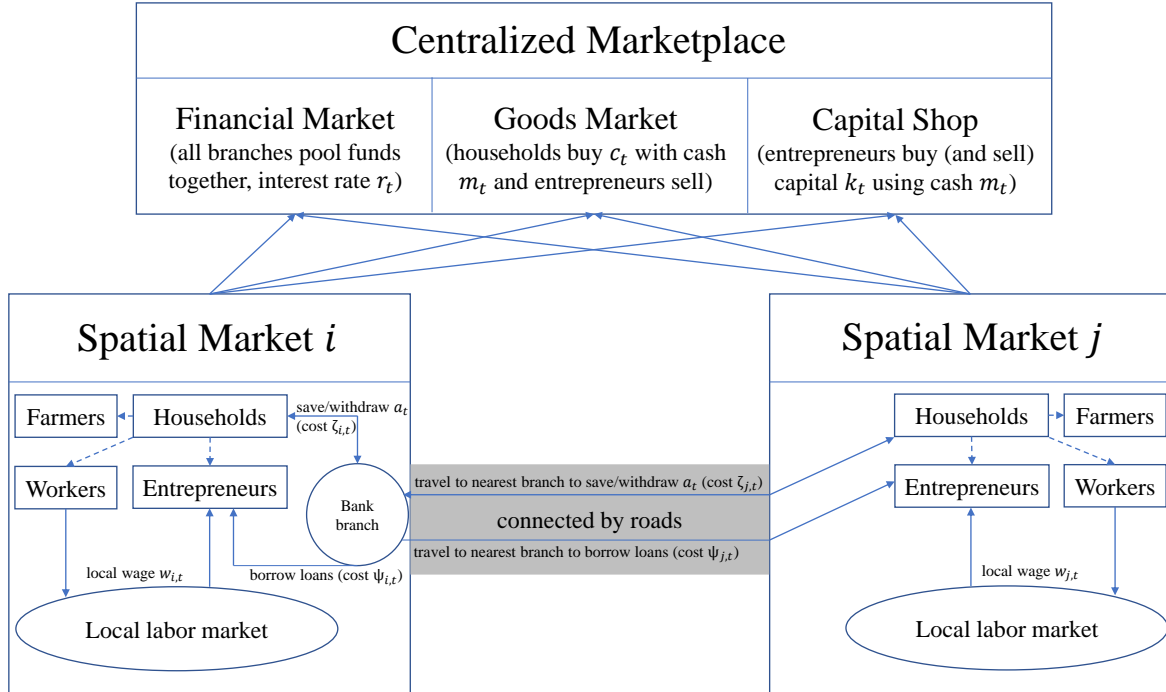## B. Circular flow across local spatial markets

Figure 4: Circular flow of the model.

where the integration is taken over all households of type $s = \{z, m, a\}$ using the CDF $\Psi_{i,t}(s)$ of market i. The indicator function $\mathbb{1}_{\{k_{i,t}(s) \geq m - \psi_{i,t}\}}$ restricts the integration to entrepreneurs who demand loans. The demand for bonds from market i is given by $D_{i,t}$,

$$D_{i,t} = \Pi_i \int a \, \mathrm{d}\Psi_{i,t}(s). \tag{3.17}$$

iv). The equilibrium wage $w_{i,t}$ is determined by taking into account two cases. If the demand for workers $\int l_{i,t}(s) \mathrm{d}\Psi_{i,t}(s)$ is smaller than the measure of non-entrepreneurs $\int \mathbb{1}_{\{V_{i,t}(s) > E_{i,t}(s)\}} \mathrm{d}\Psi_{i,t}(s)$ in market i, we have $w_{i,t} = f$ because there is an excess supply of potential workers (due to the existence of farmers). Otherwise, we have $w_{i,t} > f$, and the local wage $w_{i,t}$ is determined by the labor-market clearing condition in market i:

$$\int \mathbb{1}_{\{V_{i,t}(s) > E_{i,t}(s)\}} \mathrm{d}\Psi_{i,t}(s) = \int l_{i,t}(s) \mathrm{d}\Psi_{i,t}(s). \tag{3.18}$$

v). The joint distributions $\Psi_{i,t}(s)$ in each market i evolve according to the equilibrium allocation of quantities and prices. The set Φ_t consisting of markets with bank branches evolves according to $\Phi_t = \Phi_{t-1} \cup \Phi_t^{new}$.

3.5 Illustration of Model Mechanisms

Our model incorporates multiple markets to focus on the analysis of a spatial equilibrium. Dynamic bank expansion reduces the local credit entry cost $\psi_{i,t}$ and portfolio adjustment cost $\zeta_{i,t}$, which affects the distribution of loans and bonds across markets, consequently influencing households' occupation choice and income. In this section, we shed light on the model mechanisms by presenting households' choice of occupations, loans, and portfolio composition (cash/bonds) for different values of $\psi_{i,t}$ and $\zeta_{i,t}$. For clarity, we focus on a partial-equilibrium setting with fixed interest rate r_t and local wage $w_{i,t}$.

Occupation and Borrowing Boundaries. Panel A of Figure 5 depicts the occupation and borrowing decisions of households with different values of $m_t + a_t$ (x-axis) and z_t (y-axis), given $a_t/(m_t + a_t)$ as fixed.[22] Panel B complements panel A by representing $m_t + a_t$ along the x-axis and $a_t/(m_t + a_t)$ along the y-axis, given z_t as fixed. Households' occupation and borrowing decisions can be sufficiently summarized by the occupation boundary and the borrowing boundary.

First, consider the case with $\psi_{i,t} = 1.5$. In panel A (B), households to the southwest

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[22]Households are characterized by $s_t = \{z_t, m_t, a_t\}$. To explain the intuition, we change variables and focus on talent z_t, total wealth $m_t + a_t$, and bond-wealth ratio $a_t/(m_t + a_t)$.
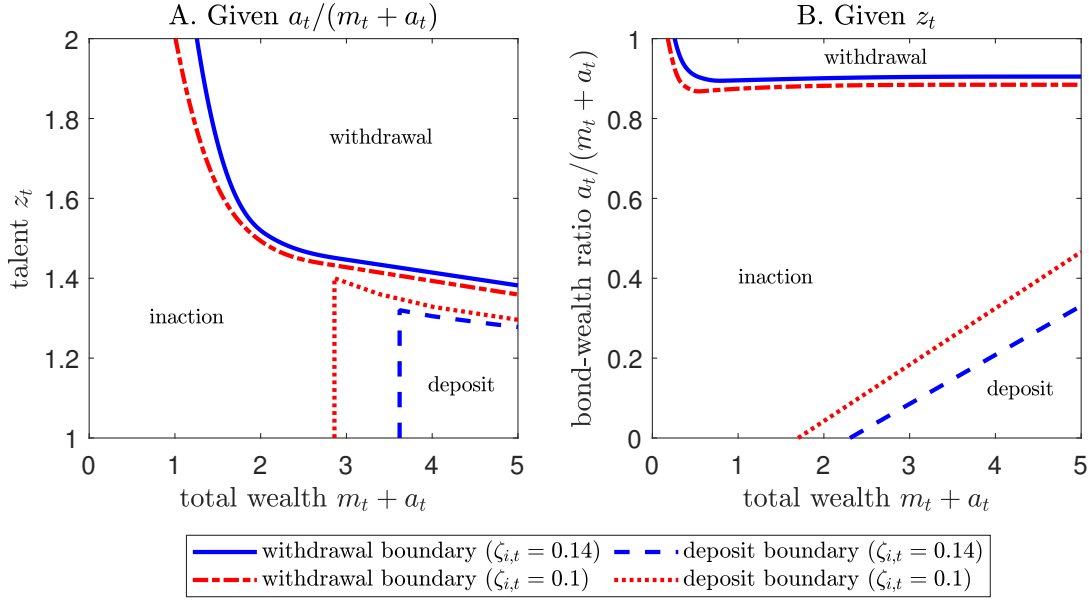
A. Given $a_t/(m_t + a_t)$

B. Given z_t
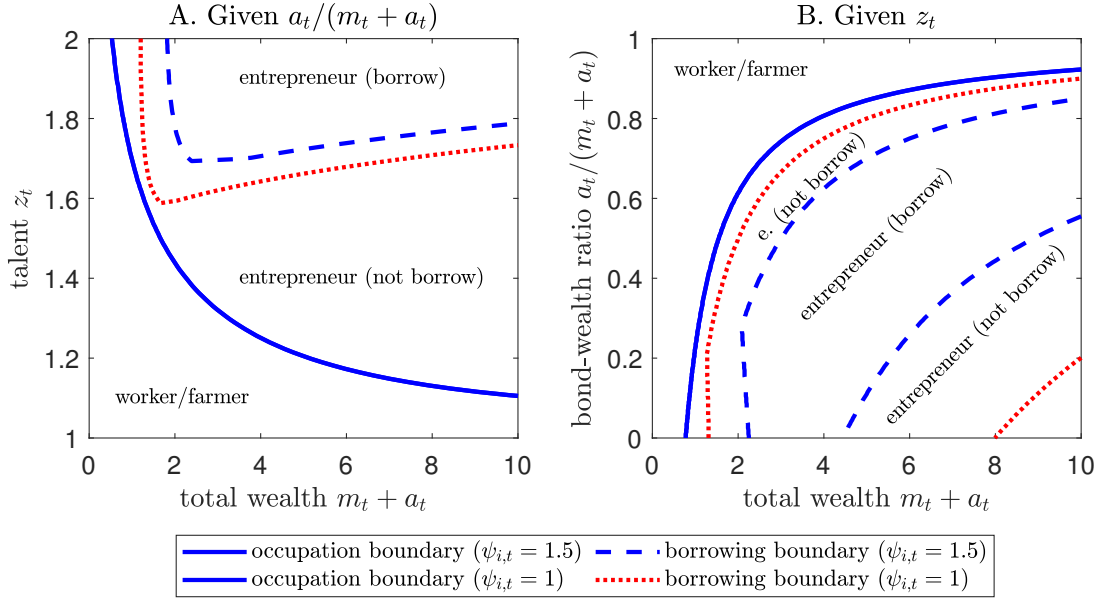
Note: This figure illustrates occupation choice and borrowing decisions for households of different types (z_t, m_t, a_t). The x-axis is total wealth $m_t + a_t$ for both panels. In panel A, we set the bond-wealth ratio at $a_t/(m_t + a_t) = 0.165$, corresponding to the median value across markets, and vary talent z_t along the y-axis. In panel B, we set $z_t = 1.73$, corresponding to the median value of entrepreneurs, and vary $a_t/(m_t + a_t)$ along the y-axis. We set the portfolio adjustment cost at $\zeta_{i,t} = \infty$ so that adjustment decisions are irrelevant. We set $r_t = 8.3\%$ and $w_{i,t} = 0.787$, corresponding to the median value across markets in 1986. The other parameter values are set according to our calibration in Section 4.

Figure 5: Occupation and borrowing decisions.

(northwest) of the occupation boundary (blue solid line) choose to be workers or farmers because they do not have sufficient wealth to start a profitable business, whereas households to the northeast (southeast) choose to be entrepreneurs. In panel A, the occupation boundary is downward sloping, indicating that more talented households require less wealth to become entrepreneurs because their businesses can be profitable at smaller scales due to higher productivity. In panel B, the occupation boundary is upward sloping, implying that households with a higher bond-wealth ratio need more total wealth to start a profitable business due to the illiquidity of bonds (i.e., buying capital requires cash).

The blue dashed lines in each panel indicate the borrowing boundaries, which are to the right of the occupation boundary because only entrepreneurs can obtain bank loans. Entrepreneurs in the region enclosed by the borrowing boundary pay the credit entry cost $\psi_{i,t}$ to borrow. The left-part of the borrowing boundary (up to the bend) in panel A and the left borrowing boundary in panel B indicate the minimum amount of cash that allows the entrepreneur to pay $\psi_{i,t}$. The right part of the borrowing boundary in panel A and the right borrowing boundary in panel B are upward sloping, indicating that entrepreneurs with greater total wealth choose to borrow only if they are more talented or have higher

Note: This figure illustrates the portfolio adjustment decisions for households of different types (z_t, m_t, a_t). The x-axis is total wealth $m_t + a_t$ for both panels. In panel A, we set the bond-wealth ratio $a_t/(m_t + a_t) = 0.165$, corresponding to the median value across markets, and vary talent z_t along the y-axis. In panel B, we set $z_t = 1.19$, corresponding to the median value of households, and vary $a_t/(m_t + a_t)$ along the y-axis. We set the credit entry cost at $\psi_{i,t} = \infty$ so that borrowing decisions are irrelevant. We set $r_t = 8.3\%$ and $w_{i,t} = 0.787$, corresponding to the median value across markets in 1986. Other parameter values are set according to our calibration in Section 4.

Figure 6: Portfolio adjustment decisions.

bond-wealth ratios, because production technology (3.3) exhibits diminishing returns to scale. Entrepreneurs in the region not enclosed by the borrowing boundaries do not borrow, either because they do not have enough cash to pay $\psi_{i,t}$ or because the benefit from loans is less than the credit entry cost.

Moving from the case with $\psi_{i,t} = 1.5$ to the case with $\psi_{i,t} = 1$, we see that the occupation boundary remains unchanged, but the borrowing boundaries in both panels shift outward (from the blue dashed lines to the red dotted lines), implying that more entrepreneurs obtain loans when the credit entry cost $\psi_{i,t}$ is lower. Thus, when all else is equal, bank expansion leads to a higher credit access ratio by reducing $\psi_{i,t}$.

Portfolio Adjustment Boundaries. While the credit entry cost $\psi_{i,t}$ largely determines households' occupation and borrowing decisions, the portfolio adjustment cost $\zeta_{i,t}$ mostly determines households' portfolio adjustment decisions. Figure 6 illustrates households' withdrawal and deposit boundaries.

Focusing on the case of $\zeta_{i,t} = 0.14$, households above the withdrawal boundary (blue solid lines in panels A and B) withdraw (i.e., convert a fraction of their bonds to cash). Intuitively,

in panel A, given the same total wealth $m_t + a_t$, households with higher talent z_t operate businesses with higher returns, which motivates them to withdraw to buy more capital. The withdrawal boundary is downward sloping because more talented households are more eager to withdraw at lower wealth levels due to the higher returns from their businesses. In panel B, given $m_t + a_t$, households with higher bond-wealth ratios withdraw because they need cash to buy consumption goods or capital.[23]

The blue dashed line in each panel indicates the deposit boundary. Households in the lower-right region enclosed by the deposit boundary make a deposit (i.e., convert a fraction of their cash to bonds). These households have high wealth and hold much more cash than they need, either because their talent is low (panel A) or because their bond-wealth ratio is low (panel B). Thus, they choose to put some of their cash into the bank to earn interests.

The remaining region indicates inaction. Households in this region keep their current portfolio of cash and bonds unchanged to save the portfolio adjustment cost $\zeta_{i,t}$. Moving from the case with $\zeta_{i,t} = 0.14$ to the case with $\zeta_{i,t} = 0.1$, we see that both the withdrawal and deposit regions expand and the inaction region shrinks, as households choose to optimize their portfolios more frequently when the cost of doing so is lower.

4   Calibration

Because we are interested in the fast growth period between 1986-1996, we do not consider the 1997 financial crisis in our baseline specification. However, in Online Appendix 3.6, we show that the model-implied transitional dynamics between 1986-1996 would be virtually unchanged even if households fully anticipated the 1997 financial crisis. Parameters are either determined from external information without simulating the model (panel A of Table 1) or calibrated internally from moment matching (panel B of Table 1). Each period represents one year.

Externally Determined Parameters.   We calibrate the initial locations of the 406 bank branches in 1986 directly according to the data. 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 Bank of Thailand for the period 1986-1996. Following standard practice, we set the risk aversion parameter to be $\sigma = 1.5$. We set the production technology parameters at $\alpha = 0.33$ and $\nu = 0.14$ according to the estimate of Paweenawat and Townsend (2019) based on the Townsend Thai data. The one-year depreciation rate δ is set as 0.08

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[23]When the total wealth $m_t + a_t$ is very low, households do not withdraw even when the bond-wealth ratio is very high, because the benefit of having more cash is outweighed by the portfolio adjustment cost $\zeta_{i,t}$.

Table 1: Calibration and parameter choice.

Panel A: Externally determined parameters					
Parameter	Symbol	Value	Parameter	Symbol	Value
Risk aversion	σ	1.5	Capital share	α	0.33
Return-to-scale	ν	0.14	Depreciation rate	δ	0.08
Liquidation loss rate	ξ	0.05	Branch capacity (people/km^2)	h	300
Interest rate spread (%)	χ	4.82			

Panel B: Internally calibrated parameters					
Parameter	Symbol	Value	Moments	Data	Model
Persistence of talent	γ	0.7	Num. of years in current business	4.0	4.1
Tail parameter of talent distbt.	ρ	4	Top 20% employment	0.72	0.71
Discount rate	β	0.89	Interest rate in 1986	0.083	0.083
Subsistence income	f	0.79	Fraction of farmers in 1986	0.46	0.47
Credit entry cost (constant)	ψ_a	0.86	Frac. of households with loans (%)	1.63	1.63
Credit entry cost (slope)	ψ_b	0.36	Sensitivity of loan access to $\nu_{i,t}$	-0.39	-0.40
Portfolio adj. cost (constant)	ζ_a	0.1	Average deposit-cash ratio (%)	27	27
Portfolio adj. cost (slope)	ζ_b	0.00125	Sensitivity of deposit-cash ratio to $\nu_{i,t}$	-0.99	-1.05

according to the estimate of Samphantharak and Townsend (2009). We set the liquidation loss rate $\xi = 0.05$ according to the structural estimate of Paulson and Townsend (2004). The market size Π_i of each market i is represented by its population density and estimated directly from the data (see Online Appendix 1.3).[24] We set the capacity of bank branches h at 300 people per square kilometer.[25] This parameter determines the interdependence of profits among branches. In Online Appendix 2.4, we discuss how it affects the model's prediction for new branch locations.

Internally Calibrated Parameters. The remaining parameters are calibrated by matching relevant moments. We solve and simulate the entire transition path from the initial distribution of households and bank branches in 1986 until the economy reaches the steady state corresponding to the branch locations in 1996. 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

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

[25]The median population density is 150 people per square kilometer across the 1,428 markets in the data. Setting $h = 200$ or $h = 400$ does not change our quantitative results much.

model needs to be solved and simulated again whenever parameters are changed because households are forward looking. As a benchmark, we specify that the economy is in a steady state in 1986. Thus, GDP would remain constant if there were no financial reforms thereafter. All of 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 persistence of talent γ determines the frequency with which entrepreneurs quit their businesses. In the Townsend Thai annual survey, entrepreneurs stay in their current businesses for about 4.0 years. We calibrate $\gamma = 0.7$ so that the model-implied moment is 4.1 years. The tail parameter ρ governs the distribution of talent, which affects entrepreneurs' relative business income and employment. We estimate that the top 20% of Thai manufacturing firms in the World Bank Enterprise Survey have a 0.72 employment share. We calibrate $\rho = 4$ to generate roughly the same employment share in the model. The initial interest rate of commercial banks is 8.3% in the data, and we calibrate the discount rate $\beta = 0.89$ to match it. The level of subsistence income f determines the fraction of farmers in 1986, which is estimated to be 0.46 in the data. We calibrate $f = 0.79$ to match this moment.

Because the credit entry costs $\psi(v_{i,t})$ and portfolio adjustment costs $\zeta(v_{i,t})$ are not directly observable, we calibrate their values through indirect inference. We assume that both $\psi(v_{i,t})$ and $\zeta(v_{i,t})$ are linear functions of $v_{i,t}$, $\psi(v_{i,t}) = \psi_a + \psi_b v_{i,t}$ and $\zeta(v_{i,t}) = \zeta_a + \zeta_b v_{i,t}$.[26] The parameters ψ_a and ζ_a determine the overall costs of obtaining credit access and adjusting portfolios. We calibrate their values at $\psi_a = 0.86$ and $\zeta_a = 0.1$ so that the model-implied average fraction of households with loans is 1.63% and households' deposit-cash ratio at the country level is 27%, which are in line with the values estimated for the 1986 data. The parameters ψ_b and ζ_b determine the sensitivity of the fraction of households with loans and the households' deposit-cash ratio to distance. To calibrate these two parameters, in the data, we estimate the panel regressions by regressing the village-level credit access conditions and deposit-cash ratios on the villages' distance from the nearest bank branch. Column (1) of Table 2 shows that a one-minute increase in car travel time (i.e., about 0.7 kilometers) is associated with a 0.64% decrease in the probability of households accessing commercial bank loans at the village level. In column (2), we further control for township and year fixed effects to capture the variation in the distance from the nearest bank branch over time caused

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[26]We are conscious that the functional forms of $\psi(v_{i,t})$ and $\zeta(v_{i,t})$ can affect the quantitative implications of bank expansion in our model. However, estimating the relationships between access to bank loans, savings in the bank, and distance from the nearest branch nonparametrically requires detailed household data. Without such high-quality data, a linear functional form seems to be a useful benchmark that can be mapped directly onto our linear regression coefficients. The quantitative implications vary little if we instead specify an exponential functional form, with the parameters calibrated to match the same moments. More flexible functional forms are more difficult to identify due to the larger number of parameters.

Table 2: Relationships between branch, credit access, and deposit-cash ratios.

	(1)	(2)	(3)	(4)
	Access to bank loans (%)		Deposit-cash ratio (%)	
Distance from the nearest branch	−0.64	−0.39	−1.16	−0.99
	(−20.29)	(−10.69)	(−8.24)	(−6.54)
Year fixed effect		$\checkmark$		$\checkmark$
Township fixed effect		$\checkmark$		$\checkmark$
Observations	186,784	186,784	2,576	2,576
R^2	0.021	0.265	0.096	0.198

Note: Columns (1) and (2) use the village-year observations of the CDD data from 1986 to 1996. Columns (3) and (4) use the village-month observations of the Townsend Thai data from August 1998 to December 2011. Because households living in the same villages are at an identical distance from the nearest bank branch, we first aggregate the ratios of households' savings in the bank to cash at the village level. t-statistics are reported in parentheses.

by new branch openings. The results remain statistically significant and have comparable economic magnitudes. Columns (3) and (4) show that a one-minute increase in car travel time is associated with an approximate 1% decrease in the deposit-cash ratio. In the model, we run similar regressions using market-level simulated data. We calibrate $\psi_b = 0.36$ and $\zeta_b = 0.00125$ so that the model-implied regression coefficients on the distance from the nearest bank branch are consistent with the estimates in columns (2) and (4) of Table 2.

Finally, we calibrate the cost of opening branches ω_t in each year so that the number of new branches n_t implied by the model is the same as that in the data in each year from 1987 to 1996 (panel A of Figure 1). These costs are not reported in Table 1, but can be computed after solving the model (see Online Appendix 2.5). Thus, our calibration is essentially equivalent to assuming that banks choose locations of new branches in each year from 1987 to 1996 given the number of branches n_t observed to open in the data. We set high costs ω_t after 1996 to ensure that the eventual steady state of the economy is consistent with the branch locations in 1996.[27]

5   Model Validation

Our calibration does not target moments along the transitional path from 1987 to 1996; these data are saved to validate our model's quantitative implications. We validate the model in three steps. In Section 5.1, we show that the model-predicted branch locations are reasonably consistent with the data. In Section 5.2, we compare the model-predicted

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[27]In Online Appendix 3.5, we verify that allowing banks to continue opening new branches from 1997 to 2011 has a negligible impact on the transitional dynamics from 1986 to 1996.

transitional dynamics with the data. In Section 5.3, we compare the model-predicted credit access conditions and entrepreneurial activity across regions with those in the data. In Sections 5.2 and 5.3, we also provide interpretations through the lens of the model.

5.1 Bank Branches: Model vs. Data

In Figure 7, we compare the model-predicted branch locations in 1996 with those in the data. Panel A displays the branch locations in the data. The yellow dots represent the 406 branch locations in 1986, which are taken as given in our model calibration. The red dots represent the locations of 431 new branches opened from 1987 to 1996. As explained in Section 2.2, there are 1,428 markets in total, defined based on the same number of branch locations observed in 2011. Our model predicts the locations of these 431 new branches opened from 1987 to 1996 of the 1,022 (1,428−406) markets that do not have branches in 1986.[28]

Panel B assesses the predictive power of the model. Our model correctly predicts the locations of 324 (gold dots) of the 431 new branches opened from 1987 to 1996, with a correct prediction ratio of 75.17% (= 324/431). We show that as a benchmark without predictive power, the median correct prediction ratio would be 42.2% if the locations of new branches were randomly selected (see Online Appendix 2.3). Clearly, our model outperforms random predictions by a wide margin.

A closer look at panel B reveals a spatial pattern of under- and over-prediction: the model predicts fewer branches around Bangkok than are found in the data (black dots around Bangkok), but predicts more branches in eastern Thailand relative to the data (purple dots). In reality, a branch can only serve a limited number of customers at each time; thus, in the data, it is natural to observe more branches in the populous Bangkok metropolitan area. Our model captures the idea of branch capacity using the parameter h, which restricts households from traveling to nearby markets to obtain financial services if those markets' population densities are already higher than h. Without imposing the capacity constraint (i.e., setting $h = \infty$), the model would predict even fewer branches around Bangkok.[29]

To assess the model-predicted timing of branch expansion, we compute the difference between the actual branch opening year and the predicted branch opening year for each market. The average difference is 3.01 years across all markets, indicating that the average model-predicted branch opening time is about 3 years different from that in the data. We

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[28]Note that even in 1996, there are 591 markets that do not have branches, as given by the total number of markets less the number in 1986 and newly established (1,428−406 − 431 = 591).

[29]In Online Appendix 2.4, we show that modeling branch capacity significantly increases the number of branches opened around Bangkok, making the model more consistent with the data. In principle, it is possible to further improve the prediction of branches around Bangkok by incorporating more sophisticated branch capacity constraints, such as by allowing h to differ across markets.

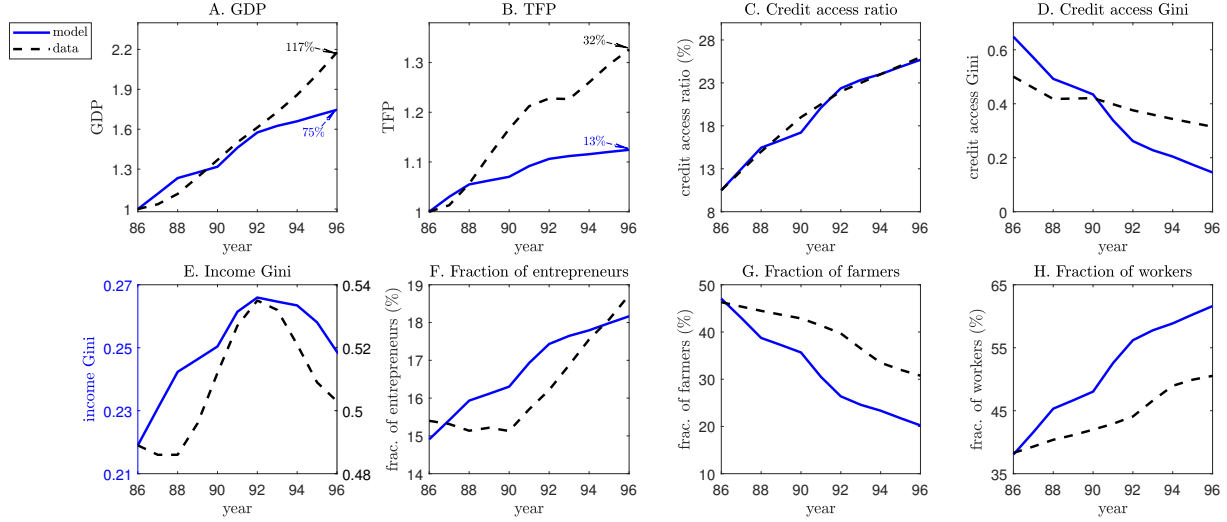|	A. Bank branches in the data		B. Model predictions	
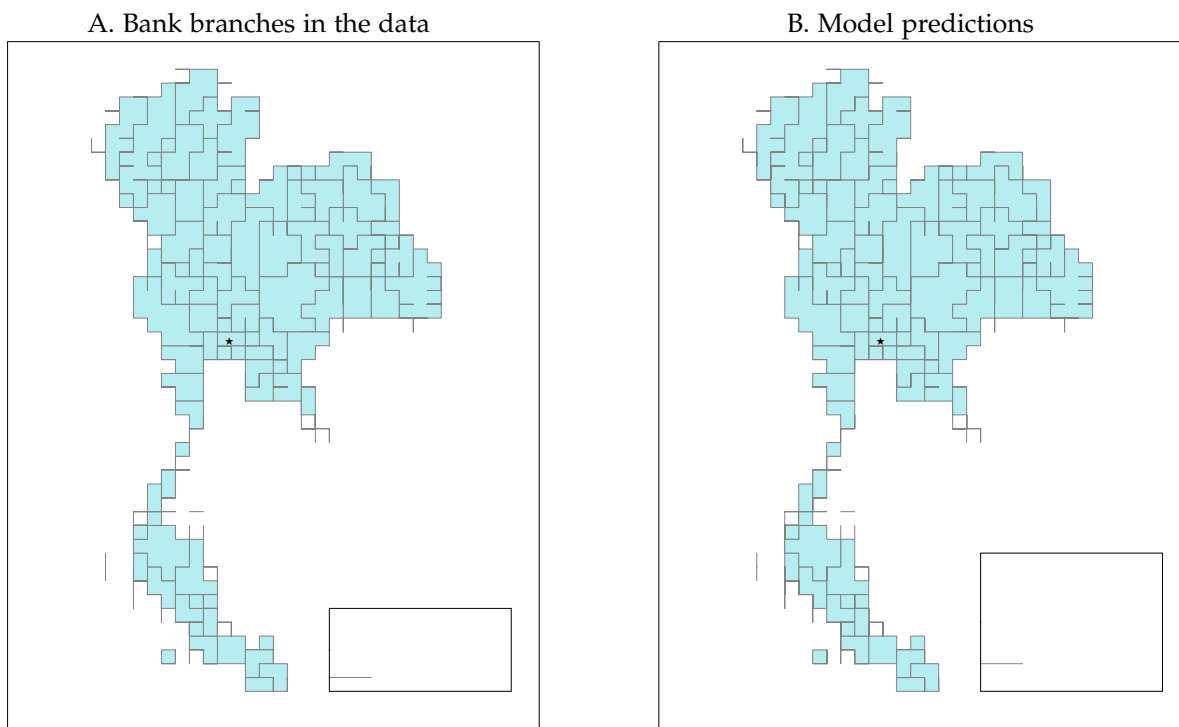
Note: Panel A displays the branch locations in the data. The yellow dots represent the 406 branch locations in 1986, which are taken as given in our model calibration. The red dots represent the locations of 431 new branches opened from 1987 to 1996. Panel B displays the model-predicted locations of the new branches opened from 1987 to 1996. The gold dots (324 in total) represent the branch locations for which the model's predictions are consistent with the data. The purple dots (107 dots) represent the locations where there are branches in the model but not in the data. The black dots (107 dots) represent the locations where there are branches in the data but not in the model.

Figure 7: Model vs. data: The distribution of bank branches.

further show that even within provinces, our model has reasonably good prediction accuracy for the dynamics of bank expansion (see Online Appendix 3.3).

5.2 Transitional Dynamics: Model vs. Data

Figure 8 displays the model's prediction for transitional dynamics in Thailand from 1986 to 1996. Panel A shows that the model implies a GDP growth of 75% over the decade caused purely by bank expansion, compared with 117% in the data. This unexplained GDP growth could be due to various factors not captured by our model, such as technological progress. The model-implied cumulative TFP growth (defined in equation (2.6) of Online Appendix 2.6) is 13% (panel B) whereas it is 32% in the data. In the model, endogenous TFP growth is driven entirely by the improved allocation of capital to entrepreneurs, as the talent distribution is

A. GDP B. TFP C. Credit access ratio D. Credit access Gini

E. Income Gini F. Fraction of entrepreneurs G. Fraction of farmers H. Fraction of workers

Note: In the model, GDP and TFP are measured by equations (2.5) and (2.6) in Online Appendix 2.6. In both the model and data, the credit access ratio is the fraction of entrepreneurs with bank loans, credit access Gini is the Gini index of market-level credit access ratio across all markets, and income Gini is the Gini index of households' income for all households in the economy.

Figure 8: Model-implied aggregate and distributional dynamics during transitions.
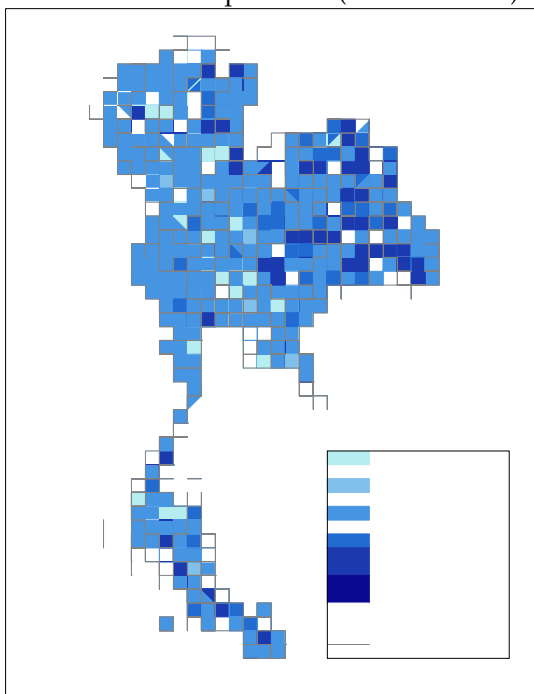
fixed over time.

Panels C and D show that our model captures the upward trend in the credit access ratio and the downward trend in credit access inequality across markets, and the magnitudes are comparable to the data. As Panel F shows, the fraction of entrepreneurs increases from 14.9% to 18.2% in the model, similar to the trend in the data. There is a strong labor transition from farming into wage work in both the model and the data (panels G and H).[30] Intuitively, opening a local branch leads to a lower credit entry cost $\psi_{i,t}$ in nearby markets, which encourages entrepreneurs to obtain bank loans and produce more. The higher local labor demand boosts the local wage, motivating farmers to leave the agricultural sector and become workers.

Our model also generates hump-shaped dynamics for the income Gini as in the data (panel E).[31] These hump-shaped dynamics are generated by two forces in the model. First, bank expansion increases entrepreneurs' profits and the fraction of entrepreneurs by providing better access to finance. Because entrepreneurs already earn more than workers and farmers,

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[30]A strong transition from agricultural to non-agricultural occupations is common to the early stage development of 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.

[31]The level of income Gini implied by the model is about half of that in the data due to the lack of worker heterogeneity. Jeong and Townsend (2008) show that the standard occupation choice model does not generate a high income Gini due to the lack of worker heterogeneity. Cagetti and Nardi (2006) introduce heterogeneity in both working ability and entrepreneurial ability to match the high Gini coefficient of earnings.

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A. Fraction of entrepreneurs (model − data)   B. Households with loans (model − data)
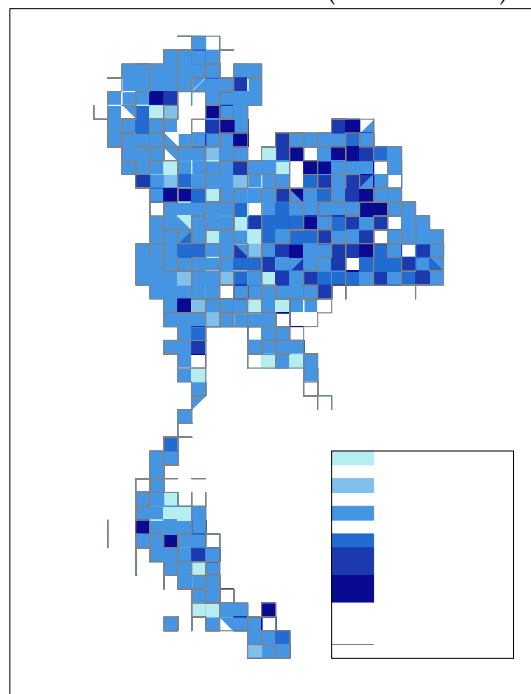
Note: Panel A presents the percentile-rank difference in the fraction of entrepreneurs between the data and model. In both the model and the data, we calculate the percentile rank of each market (ranging from 0% to 100%) out of all of the markets in terms of the market-level fraction of entrepreneurs. We then depict the percentile-rank difference (model minus data) using different colors (from light blue to dark blue). For example, the darkest blue color indicates that the percentile in the model is more than 25% higher than that in the data, meaning that the model overpredicts the market's fraction of entrepreneurs. Similarly, the lightest blue shows the greatest underprediction. Panel B similarly plots the percentile-rank difference in the fraction of households with commercial bank loans between the model and the data.

Figure 9: Model vs. data: Fraction of entrepreneurs and household loan access.

and there are relatively few of them initially, further increasing their incomes leads to a higher Gini coefficient. Second, bank expansion results in a large labor transition as many farmers are hired by entrepreneurs and become workers. Because farmers earn less than workers (after wage takeoffs) and entrepreneurs, and there are many more of them initially, increasing their income leads to a lower Gini coefficient. We decompose the drivers of income Gini dynamics in Online Appendix 3.1.[32]

5.3 Regional Heterogeneity: Model vs. Data

The financial deepening caused by bank expansion directly motivates entrepreneurial activity and business startups. We examine the goodness-of-fit for the model's out-of-sample predictions of the distribution of entrepreneurial activity and credit access conditions across markets by 1996. In both the model and the data, we calculate the percentile rank of each market (ranging from 0% to 100%) out of all markets in terms of the market-level fraction of entrepreneurs or fraction of households with commercial bank loans. Figure 9 shows that our model has a good overall fit with the data. A large fraction of Thailand is shaded mid-light/mid-dark blue, representing regions whose percentile-rank difference (model minus data) is less than 10%. Our model captures the high concentrations of entrepreneurial activity and loan access around Bangkok and south and north of this area along Thailand's central corridor, as well as the low concentrations of both in the northeast (see Online Appendix 1.4 for patterns in the data).

6 Model-Based Evaluation

We use the calibrated model to shed further light on the implications of bank expansion. Section 6.1 provides a decomposition of growth and inequality and assesses the welfare consequences of bank expansion across regions. Section 6.2 presents the model's implications regarding the flow of funds across local spatial markets. Section 6.3 quantifies the credit provision and deposit mobilization channels of bank expansion.

6.1 Decomposition of Growth, Inequality, and Welfare

Panel A of Figure 10 decomposes the GDP growth from 1986 to 1996 by factor (the formulas are presented in Online Appendix 2.6). A major part (41.5%) of the 75% cumulative GDP growth implied by the model is attributable to labor growth, which coincides with the pattern in panel H of Figure 8. About 19.5% of cumulative GDP growth is attributable to capital growth, and the remainder is attributable to TFP growth.

Panel B of Figure 10 decomposes the GDP growth by credit regime. Bank expansion promotes GDP growth by enabling entrepreneurs who were previously excluded from the credit market to borrow loans (extensive margin) and entrepreneurs who already had credit access to expand their businesses (intensive margin). The former contributes about 57.4% of

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[32]The Gini coefficient does not capture the entire distribution of income, especially the higher-order moments and tail distributions (Guvenen et al., 2015, 2017). Our decomposition aims helps uncover forces behind the income Gini dynamics in the model.

A. Growth accounting by factor B. Growth accounting by credit regime C. Growth accounting by market
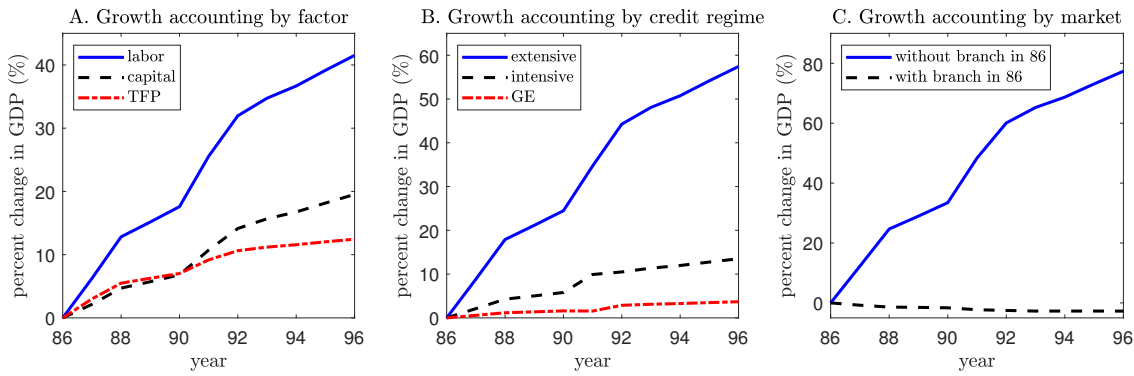
Note: Panel A decomposes the GDP growth by factor (labor, capital, and TFP) according to a standard growth accounting exercise. Panel B decomposes the GDP growth by credit regime as in Dabla-Norris et al. (2020). The extensive margin refers to the GDP growth resulting from entrepreneurs obtaining credit access after bank expansion. The intensive margin refers to the GDP growth resulting from entrepreneurs who already had credit access expanding their production after bank expansion. The general equilibrium effect (GE) is a residual term. Panel C decomposes the GDP growth by market, i.e., the markets without branches in 1986 versus those with branches in 1986. The formulas for the decomposition in each panel are provided in Online Appendix 2.6.

Figure 10: Decomposition of GDP growth by factor, credit regime, and market.

cumulative GDP growth and the latter contributes about 13.5%. The more important role played by the extensive margin is consistent with the dramatic increase in the credit access ratio in both the model and the data (panel C of Figure 8).

In panel C of Figure 10, we further decompose GDP growth according to geographical areas. Specifically, we separately consider the contribution to GDP growth of markets with branches in 1986 and that of markets without branches in 1986. We find that the latter group of markets accounts for all of the GDP growth, indicating the important role played by new branch openings. The former group actually experiences slight negative growth, −2%, due to the general equilibrium effects of higher interest rates.

Figure 11 analyzes the income Gini dynamics within and across markets. As panel A shows, the income inequality among entrepreneurs from different markets increases from 1986 to 1989 and decreases thereafter (i.e., the blue solid line is hump shaped). Initially, only a few markets obtain new branches. The entrepreneurs in these markets earn much higher income due to the lower credit entry costs than do those in markets without branches, which increases the cross-market income inequality. As more branches are opened over time, more entrepreneurs obtain credit access, leading to lower cross-market income inequality. By contrast, the income inequality among workers from different markets increases steadily from 1986 to 1996 (i.e., the black dashed line is upward sloping). As we discuss in Online Appendix 3.4, workers in markets with earlier branch openings experience a wage takeoff, resulting in higher cross-market income inequality among workers. Panel B plots the within-market income Gini dynamics of entrepreneurs and workers. The income Gini coefficient is zero for
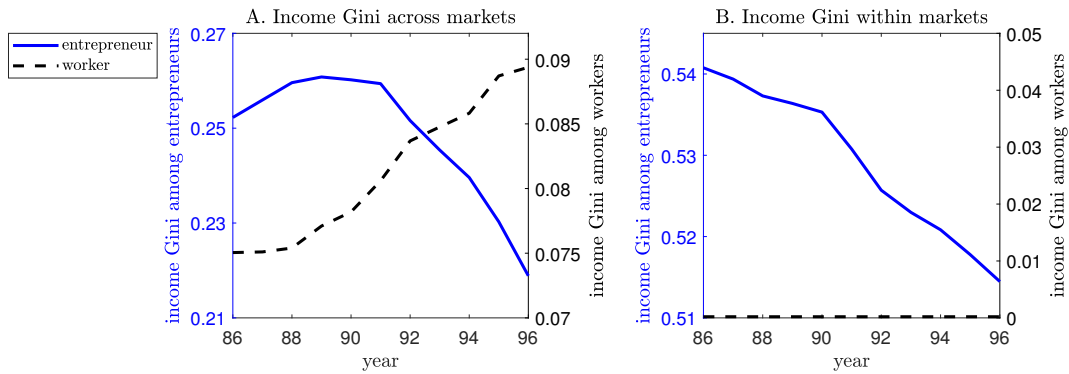
Note: Panel A plots the model-implied cross-market income Gini dynamics for entrepreneurs and workers. We first calculate the average incomes of entrepreneurs and workers in each market and each year. We then plot the Gini coefficients of average incomes of entrepreneurs and workers across the 1,428 markets from 1986 to 1996. Panel B plots the within-market income Gini dynamics for entrepreneurs and workers. We first calculate the income Gini coefficients of entrepreneurs and workers within each market in each year. We then plot the average income Gini coefficients of entrepreneurs and workers across the 1,428 markets from 1986 to 1996.

Figure 11: Income inequality within and across markets.

workers, because the same wage $w_{i,t}$ is paid to workers within the same market. The income Gini coefficient of entrepreneurs within the same market decreases steadily mainly because of the rise in the cost of capital. Bank expansion results in a higher equilibrium interest rate for entrepreneurs (the blue solid line in panel H of Figure 14), which hurts high-income entrepreneurs more because they use more capital in production.

To evaluate the welfare implications of bank expansion, we follow Jones and Klenow (2016) and calculate the growth rate of the consumption equivalent gain at the country and market levels (see Online Appendix 2.7). The overall country-wide welfare increases by 52.3% from 1986 to 1996. As Figure 12 shows, there is large heterogeneity in welfare gains across markets. The markets close to bank branches in 1986 (yellow dots) experience small improvements in the standard of living. By contrast, the markets that are initially far away from branches but obtain new branch openings (red dots) have welfare gains as large as 270%, and these markets also generally have the largest GDP and TFP growth (see Online Appendix 3.2).

6.2 Flow of Funds

The aggregate effect presented in Figure 8 masks interesting regional heterogeneity in financial deepening and the levels of assets and liabilities. Figure 13 zooms in on such heterogeneity across markets. Panel A of Figure 13 shows that most markets in 1986 lacked access to bank loans (white area) because they were far from existing branches; as a result, credit is also very unequally distributed across markets. Such regional heterogeneity underlies the low credit access ratio and the high credit access Gini coefficient for the aggregate economy (panels C
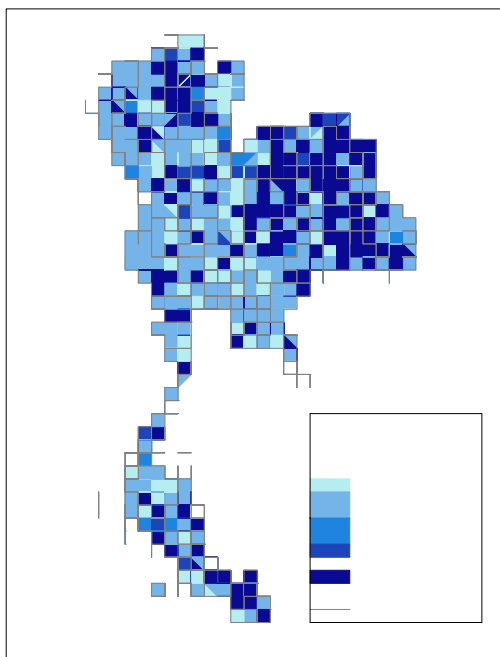
Figure 12: Model-implied market-level welfare gains from 1986 to 1996.

and D of Figure 8).

Because our model assumes free capital flows across markets, the local demand for bank loans is not necessarily equal to the local supply of funds (i.e., deposits). Panel B of Figure 13 shows that the local demand for loans is larger than the local amounts of deposits in the regions close to bank branches (dark/light blue), indicating that capital flows to regions with better access to finance.[33] The endogenous flow of funds implied by our model captures an important aspect of the within-country inter-regional capital flows in Thailand (Paweenawat and Townsend, 2019), as it contributes to the high inequality among entrepreneurs in different regions. The rapid bank expansion over the study decade leads to a significantly higher density of bank branches in 1996. In panel C of Figure 13, the red dots represent the newly opened bank branches from 1987 to 1996 predicted by our model. The markets close to these branches experience a dramatic increase in the local loan demand (exceeding 400%), as represented by the dark blue color.

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[33]This is implied by our calibration. In the data, the empirical relationship between the deposit-cash ratio and the distance from the nearest bank branch (columns (3) and (4) of Table 2) is weaker than that between the credit access ratio and the distance from the nearest bank branch (columns (1) and (2) of Table 2). After calibrating the portfolio adjustment cost $\zeta(v_{i,t})$ and the credit entry cost $\psi(v_{i,t})$ to match these patterns, we find that opening a branch increases the local market's demand for loans more than the increase in the amount of deposits.

| A. Loan demand in 1986 | B. Loan demand − deposits | C. Growth in loan demand |
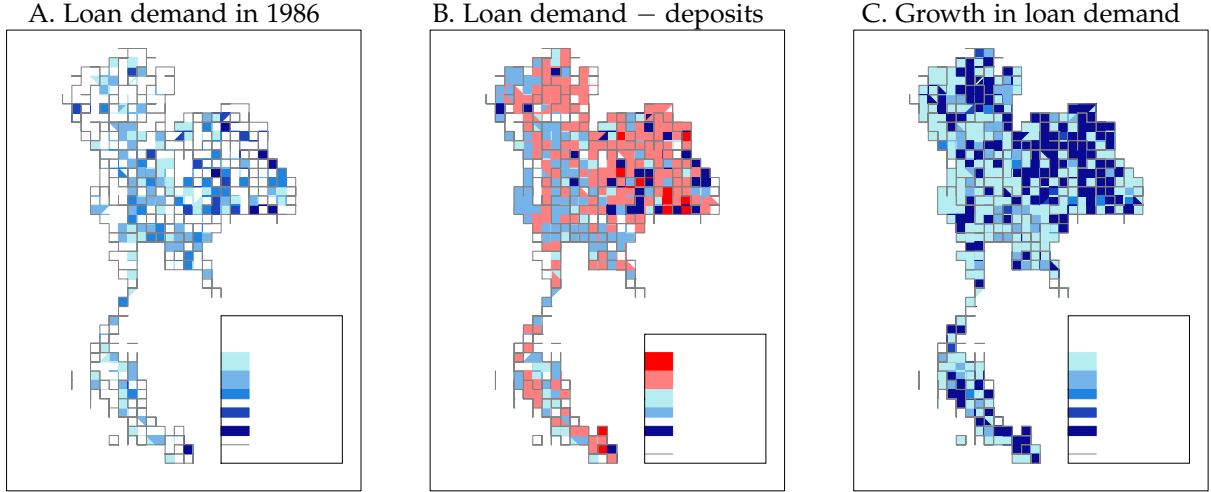
Note: Panel A plots the percentage of bank loans (i.e., local demand for loans divided by the aggregate amount of bank loans) borrowed by entrepreneurs in each local market in 1986. Panel B plots the local excess loan demand in 1986, which is defined as the difference between the local demand for loans and the local supply of funds (i.e., deposits) divided by the aggregate amount of bank deposits. The red regions have excess local supply of funds, and the blue regions have excess local demand for loans. Panel C plots the cumulative growth in local loan demand from 1986 to 1996. The yellow dots in each panel represent bank branches in 1986 and the red dots in panel C represent the new bank branches opened between 1987 and 1996.

Figure 13: Model-implied loan demand and deposits across local spatial markets.

6.3 Credit Provision vs. Deposit Mobilization

As discussed in Section 3.5, bank expansion affects the economy by allowing local entrepreneurs to obtain loans at lower credit entry costs $\psi_{i,t}$ and by increasing the supply of funds (i.e., deposits) through lower portfolio adjustment costs $\zeta_{i,t}$. In this section, we separately quantify these two channels. In Online Appendix 3.7, we quantify their distributional effects and welfare implications across markets.

The black dashed and red dotted lines in Figure 14 represent the impacts through the credit provision and deposit mobilization channels, respectively. To isolate the credit provision channel (black dashed line), we only allow the credit entry cost $\psi_{i,t}$ to decrease with new branch openings, as we keep each market's portfolio adjustment cost $\zeta_{i,t}$ fixed at its 1986 value. Similarly, to isolate the deposit mobilization channel (red dotted line), we only allow $\zeta_{i,t}$ to change, as we keep $\psi_{i,t}$ fixed at its 1986 value.

Panel A shows that the credit provision channel alone generates GDP growth of 66% over the decade, compared with 3% cumulative GDP growth from the deposit mobilization channel. The deposit mobilization channel does not seem to have a substantial impact on GDP growth for two main reasons. First, the portfolio adjustment cost $\zeta(v_{i,t})$ weakly responds to changes in the distance from the nearest bank branch $v_{i,t}$ in our calibration, as suggested by

the data (columns (3) and (4) of Table 2). Second, the impact of reducing $\zeta_{i,t}$ on GDP is only realized gradually through households' endogenous accumulation of wealth. Such transitions are very slow because of the high credit entry costs in these markets, as we discuss in Online Appendix 3.4.

Comparing the three lines in panel A, we find that there is complementarity between the two channels. Although the deposit mobilization channel alone boosts GDP little in the short run, it amplifies GDP growth through the credit provision channel. When the two channels are both active, the cumulative GDP growth is 75%, which is larger than the sum of each channel's separate effect (i.e., 66%+3% = 69%). Intuitively, deposit mobilization increases the supply of funds (i.e., loans to entrepreneurs), leading to a lower interest rate. In the absence of the credit provision channel, most markets face high credit entry costs $\psi_{i,t}$; thus many talented entrepreneurs do not have credit access. As a result, most of the additional funds provided through deposit mobilization are absorbed by less talented entrepreneurs living in markets that already had branches in 1986, exerting a limited impact on aggregate output. By contrast, with the credit provision channel, most markets face low $\psi_{i,t}$ after bank expansion, which allows talented entrepreneurs to borrow more and expand their businesses in response to a lower interest rate, improving the allocation of the additional funds.[34]

Nearly all of the TFP growth from bank expansion is attributable to the credit provision channel rather than the deposit mobilization channel (panel B). The credit provision channel generates a much more significant impact on the promotion of entrepreneurship (panel F) and reducing the fraction of farmers (panel G). The deposit mobilization channel has only a minor impact. Moreover, the credit provision channel significantly boosts economy-wide credit access ratio (panel C) whereas the deposit mobilization channel has little effect on credit access decisions.[35]

Regarding the distributional implications, panel D shows that the decreasing inequality of credit access across markets is driven entirely by the credit provision channel. As panel E shows, the deposit mobilization channel generates a steady increase in the income Gini because easier access to bond investment mainly benefits wealthier households, which already earn higher incomes. Thus, the hump-shaped Gini dynamics in panel E of Figure 8 are

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[34]In Online Appendix 3.8, we provide more simulations to support these intuitions, and we show that the complementarity is, crucially, attributable to spatial heterogeneity across markets. The complementarity also appears for other variables; not only GDP growth. In general, the quantitative impacts of this complementarity vary across variables. For example, there is strong complementarity in boosting the credit access ratio, as the credit access ratio decreases if the deposit mobilization channel works alone because some households accumulate sufficient wealth in interest-bearing accounts and become self-financed entrepreneurs. However, the credit access ratio increases from 22% to 25.7% when the deposit mobilization channel is combined with the credit provision channel. The complementarity effect on TFP is smaller primarily because of the low level of TFP growth implied by the model.

[35]The deposit mobilization channel affects credit access decisions indirectly by allowing households to accumulate wealth in interest-bearing accounts, and by changing interest rates and wages in equilibrium.
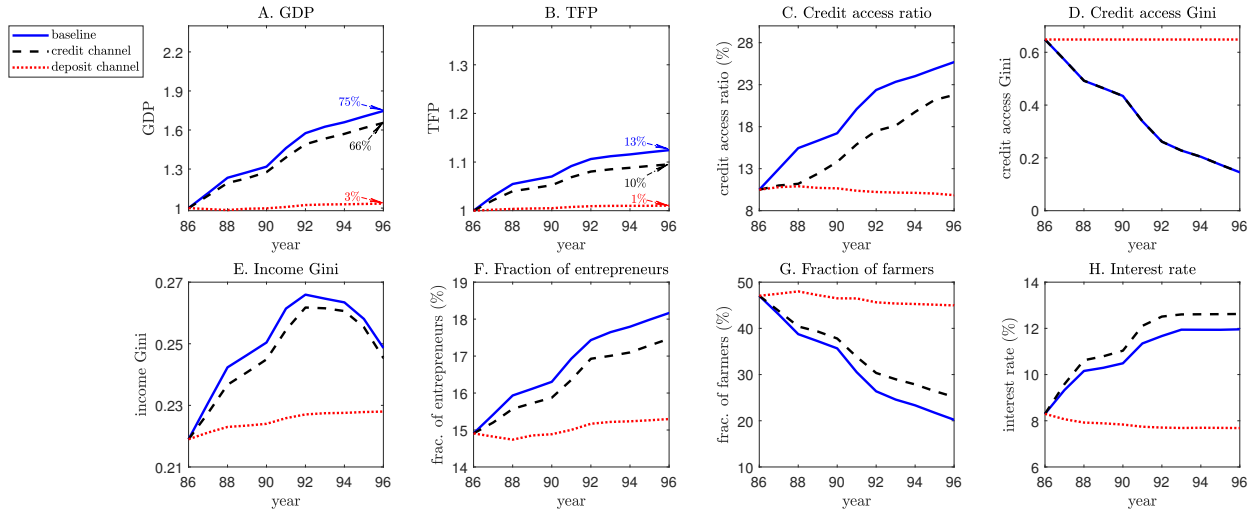
Note: The blue solid line represents the baseline model of bank expansion. The black dashed line quantifies the credit provision channel, where only the credit entry cost $\psi_{i,t}$ decreases with new branch openings and each market's portfolio adjustment cost $\zeta_{i,t}$ is fixed at its 1986 value. The red dotted line quantifies the deposit mobilization channel, where only $\zeta_{i,t}$ decreases with new branch openings while $\psi_{i,t}$ is fixed at its 1986 value.

Figure 14: Credit provision and deposit mobilization channels of bank expansion.

caused by the credit provision channel. At the aggregate level, these two channels impact the economy by shifting the supply and demand curves of aggregate capital, and they have opposite impacts on the equilibrium interest rate (panel H).

7 Digital Banking

Recent developments in fintech are leading to a new era of smart branchless banking. For example, India launched the Digital India program in 2015 to provide paperless, cashless and faceless services across the country. China announced the Internet Plus plan in 2015 to encourage the development of e-commerce, industrial networks, and Internet banking. The Hong Kong Monetary Authority approved the launch of eight digital banks in 2020. In November 2020, Brazil launched an instant payment platform (PIX) and mandated its use by all financial institutions and payment institutions that are licensed by the Central Bank of Brazil and have more than 500,000 active customer accounts. The introduction of "virtual banking" licenses has allowed non-traditional financial service providers to engage in digital banking without physical branches. Digital banking can increase financial inclusion for retail customers and for small and medium-sized enterprises as it lowers transaction costs.

As a final experiment, we use our model to predict what the subsequent transitional dynamics would be if all of the transaction costs were set at zero (i.e., $\psi_{i,t} = \zeta_{i,t} = 0$ for all i)

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forever since 1986. Figure 15 compares the implications of this digital banking experiment (black dashed line) with those of our baseline experiment with dynamic physical bank expansion (blue solid line). Immediately after the economy switches to digital banking, GDP and TFP increase significantly and continue to rise, reaching 136% and 27%, respectively, in 1996. Both the short-run and long-run impacts of introducing digital banking are much larger than the predictions of our baseline experiment with physical branches. The credit access ratio increases to 100% and the credit access Gini falls to zero because of the absence of transaction costs. As panel E shows, digital banking leads to a dramatic increase in the income Gini coefficient in the first two years because of overshooting in the equilibrium interest rate (black dashed line in panel H). However, in the long run, digital banking leads to much lower income inequality. The changes in many dimensions are not instantaneous, as it takes much longer than 10 years from the introduction of digital banking for the economy to reach its new steady state, given the underlying dynamic decisions, capital accumulation, and other factors. We present the full transitional dynamics and welfare implications of digital banking in Online Appendix 3.9.

To study the spatial implications of digital banking, in panel A of Figure 16, we plot the regional GDP relative to the national average in 1996. The variation in regional GDP across markets is fairly small, which indicates that the initial regional disparity in 1986 does not play an important role after the introduction of digital banking. In comparison, panel B of Figure 16 shows that the variation in regional GDP across regions for the baseline bank expansion remains large in 1996.

The digital banking experiment in the model captures an important aspect of CBDC administered through the commercial banking system.[36] Under this system, retail payments can be made entirely electronically, and there is no more paper currency. As shown in Figure 15, we conduct two more counterfactual experiments to provide a model-based estimate of the impact. The green dotted line corresponds to the experiment in which $\zeta_{i,t}$ is set at zero for all markets i since 1986 but $\psi_{i,t}$ decreases according to the baseline bank expansion. In this experiment, households do not hold currency for consumption because they can always obtain cash by making a free portfolio adjustment in the current period, which is effectively the same as using deposits directly to buy consumption goods. Thus, this experiment quantifies the deposit mobilization channel of CBDC. However, in the model, entrepreneurs may still hold some currency to purchase capital at the beginning of the following period. If, on top of reducing $\zeta_{i,t}$ to zero, we also reduce the credit entry cost $\psi_{i,t}$ to zero, as in the full digital banking experiment (black dashed line), then the economy can entirely get rid of currency, which corresponds to the broadest interpretation of CBDC.

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[36]For example, this is how CBDC is implemented in China.
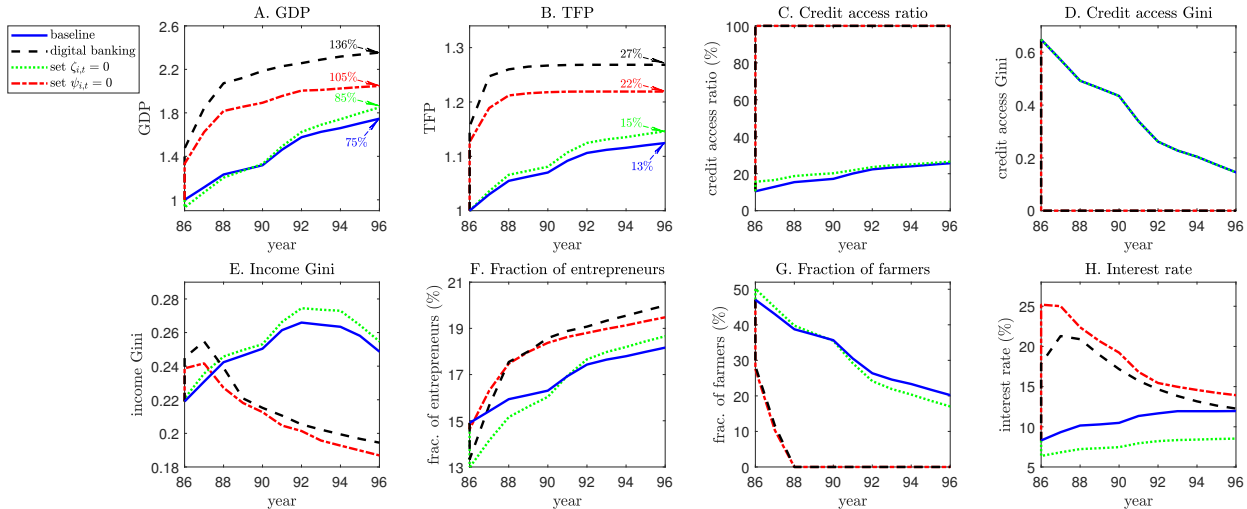
Note: The blue solid line represents the baseline model with bank expansion. The black dashed line represents the hypothetical experiment of introducing digital banking unexpectedly in 1986. We set all transaction costs to zero forever starting from 1986, i.e., $\psi_{i,t} = \zeta_{i,t} = 0$ for all i. We further decompose the impact of introducing digital banking using two counterfactual experiments. In the first experiment (green dotted line), we set portfolio adjustment costs $\zeta_{i,t} = 0$ for all i starting from 1986, and we assume that the credit entry cost $\psi_{i,t}$ decreases across markets over time according to the baseline bank expansion. In the second experiment (red dash-dotted line), we set $\psi_{i,t} = 0$ for all i starting from 1986, and we assume that $\zeta_{i,t}$ decreases across markets over time according to the baseline bank expansion.

Figure 15: Transition to digital banking.

We can further separate out the credit effect of digital banking. The red dash-dotted line corresponds to the experiment in which $\psi_{i,t}$ is set at zero for all markets i from 1986 onward, but $\zeta_{i,t}$ decreases according to the baseline bank expansion, which quantifies the impact of digital banking through the credit provision channel.[37] These experiments reveal that relative to the baseline bank expansion (blue solid line), making portfolio adjustments free boosts GDP growth by 10% (from 75% to 85%). By contrast, making credit entries free increases GDP by 30% (from 75% to 105%). Again, there is a complementarity between the two channels, because the total impact on GDP growth is 61% (136% − 75%), which is larger than the sum of the effects of each (10% + 30% = 40%).

8 Conclusion

The interaction between spatial heterogeneity and financial deepening is central to a wide range of important phenomena in the process of economic development. This paper develops

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[37]We are reluctant to term this the credit effect of CBDC, although it is in the model. In reality, there are other forms of credit costs such as the costs of processing credit applications, and screening borrowers, etc. These costs do not disappear with the introduction of CBDC.

| | A. Digital banking | B. Baseline bank expansion |
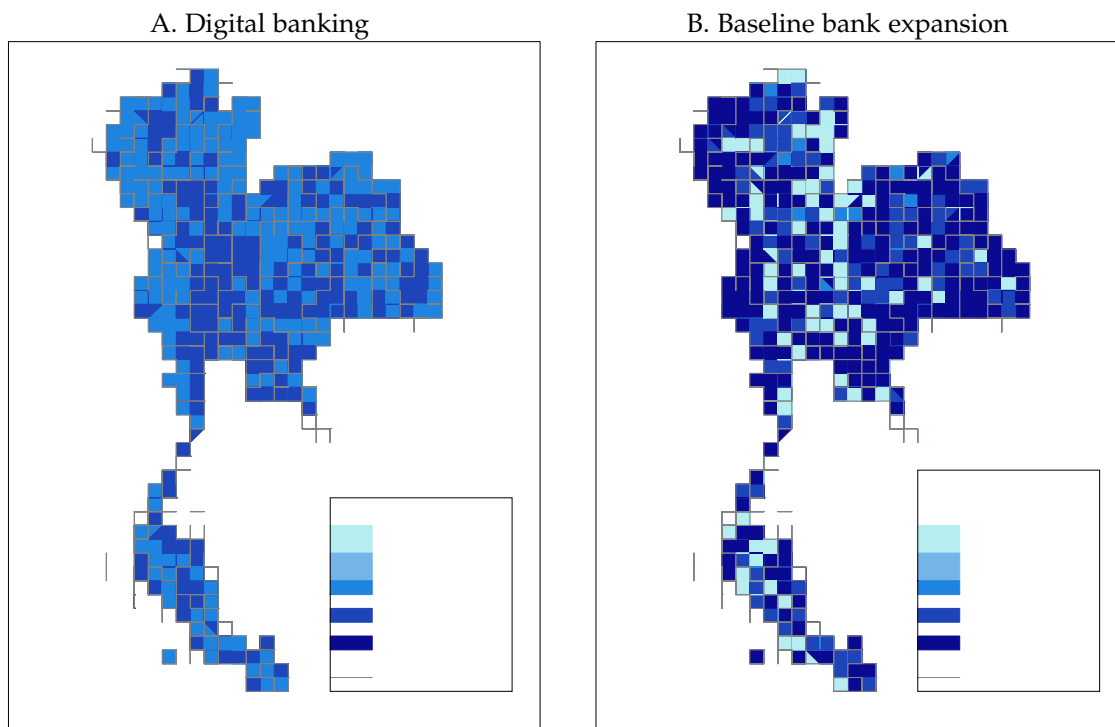
Note: Panel A plots the regional GDP relative to the national average (weighted by market size Π_i) in 1996 for the digital banking experiment where $\psi_{i,t} = \zeta_{i,t} = 0$ for all i starting from 1986. For comparison, panel B plots the regional GDP for the baseline bank expansion.

Figure 16: Spatial implications of digital banking and baseline bank expansion.

a spatial equilibrium model with heterogeneous households to study economic transitions accompanied by dynamic bank expansion, a departure from typical calibration exercises based on models without geography. To make the model computable, we propose an algorithm that solves the combinatorial problem of bank expansion numerically.

We apply the model to Thai data for 1986 to 1996, calibrate it, and make predictions. At the regional level, the model's predictions of the distribution of bank branches and the spatial concentration of enterprises and bank loans are broadly consistent with the 1996 data. At the aggregate level, the model captures the secular trends in the transition of labor from the agricultural sector to the manufacturing sector, burgeoning entrepreneurial activity, hump-shaped income Gini dynamics, increasing credit access ratio, and decreasing credit access inequality. Our confidence in the quantitative exercise is enhanced by the model's ability to capture these micro and macro facts.

The model reveals that regional heterogeneity plays a crucial role in shaping the dynamics of GDP and inequality and the flow of funds across local spatial markets. Moreover, there is complementarity between the deposit mobilization and credit provision channels of bank

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expansion. Although the deposit mobilization channel alone plays little role in boosting GDP growth, it significantly amplifies the impact of the credit provision channel. Finally, we apply the model to evaluate digital banking, which greatly reduces regional heterogeneity, quantifying the roles of deposit costs and credit costs and the complementarity between the two.

Our model should be viewed as a step toward better understanding 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, or costly migration. The framework that we propose in this paper can be enhanced in future research to clarify the roles of these forces in spatial development.

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