Bank Branch Expansion vs International Capital Flows:
Integrating Local Spatial Markets with Macro Aggregates

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Abstract

Financial reforms, as in Thailand, were typically implemented in a package that includes both the deregulation of domestic financial markets and the liberalization of international financial transactions. We develop a high-dimensional dynamic equilibrium model with 1426 spatial markets to understand, evaluate, quantify and separate the impact of these micro and macro-based financial reforms on GDP growth, financial inclusion, inequality, and welfare. In the model, agents make occupation choices, and those who run businesses face three financial frictions including an entry cost to obtain credit, a collateral constraint, and an interest rate spread. Agents optimally hold cash to purchase consumption goods, facing the tradeoff between foregone interests and transaction fees. Banks choose where to open new branches, which reduce both the entry costs and the transaction fees in nearby markets. Capital account liberalization results in capital inflows and lowers the interest rate spread. We calibrate the model using pre-reform data from five distinct datasets as well as roads and exact branch locations mounted on a Geographic Information System. We then evaluate the model’s ability to predict branch locations and several micro and macro aspects of the data. Computation of the equilibrium with both supply and demand sides of the market, endogenous distributions of wealth and bank networks, and endogenous wage and interest rates along a transition path is accomplished with a novel numerical algorithm. Counterfactual simulations suggest that both bank expansion and capital account liberalization contribute significantly to GDP growth but through different channels, and as a consequence, they have different implications on income inequality and welfare. From the bank expansion, there is a positive spatial correlation between the welfare change of workers and entrepreneurs as both benefit more if they were previously farther away from bank branches. However, the spatial correlation is negative from the capital account liberalization.

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

**Keywords:** financial frictions, local markets, bank expansion, capital flows, spatial equilibrium.

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1 Introduction

1.1 Motivation in the Context of the Literature

The nature of financial liberalization is multifaceted as financial frictions are likely to have various forms, including credit/interest rate controls, entry barriers and operational restrictions in the banking sector, as well as restrictions on international capital flows (Abiad and Mody, 2005). Financial reforms seek to alleviate these obstacles through the deregulation of domestic financial markets and the liberalization of international financial transactions. Although the motivation for these reforms has been attributed to promoting growth in savings, investment, and GDP, lately fostering financial sector policies that promote inclusive growth has been among the foremost concerns of the G20, IMF, and World Bank.

In this paper, we develop a novel dynamic equilibrium model with local spatial markets and heterogeneous agents to understand, evaluate, and quantify the impact of financial reforms on GDP growth, financial inclusion, inequality, and welfare. We thus put both micro and macro aspects on the same page. We apply our model to the rapid economic growth and financial deepening period in Thailand (1986-1996), during which a series of financial liberalization policies were adopted, resulting in fast bank branch expansion and large capital inflows.\footnote{Townsend and Ueda (2010) point out that financial liberalization in Thailand happened earlier according to the actual de facto deregulation. The standard de jure documentation of financial liberalization consists of a chronology of changes in laws regulation, which do not seem to change much in the 1980s. The de facto measures seem to capture Thai financial sector policies better. Following this, we will calibrate the exogenous policy shifts in our structural model using the observed interest rate spread, capital flows, and bank branches.} A main result is that both bank expansion and capital account liberalization contribute significantly to GDP growth but through different channels, and as a consequence, they have different implications on income inequality and welfare. Following the bank expansion, there is a positive spatial correlation between the welfare change of workers and entrepreneurs as both are benefited more if they were previously farther away from bank branches. However, the spatial correlation is negative following capital account liberalization as workers living closer to bank branches obtain relatively smaller welfare gains while entrepreneurs living in these locations experience larger gains due to better credit access.

The consensus in the literature is that resource inflows reduce the cost of capital, triggering a temporary increase in growth and a permanent increase in the level of output (Obstfeld, 1998; Rogoff, 1999; Summers, 2000; Fischer, 2003). However, the empirical evidence about the impact of capital flows on growth is mixed (Prasad et al., 2003; Henry, 2007; Mody and Murshid, 2011). Many studies suggest that international capital flows often stem from differences in financial obstacles across countries. For example, Gourinchas and Jeanne (2013) study the negative correlation between TFP and capital flows and identify a savings puzzle. Buera and Shin (2016) study the differences in the tightness of collateral constraints between the U.S. and emerging market countries. They find that an underdeveloped financial market explains the joint dynamics of TFP and capital flows following economic reforms. Our paper takes a stand on causality and quantifies the effect of capital flows through the length of an estimated structural model with multiple potential obstacles disciplined by the data.

The interest in the nexus between financial development and economic growth dates at least as far back as Schumpeter (1911). A general topic in this literature is whether finance causes growth (see
Levine, 2005, for an excellent review). In the past two decades, numerous cross-country studies, quasi-experimental designs, and randomized control trials have provided ample evidence on a causal effect. For example, King and Levine (1993) present cross-country evidence supporting the view that finance causes growth. Rajan and Zingales (1998) find financial markets reduce the cost of external finance for firms by exploring industry-level cross-country variations in financial development. Beck, Levine and Loayza (2000) retrace the views of Schumpeter (1911) and the growth accounting literature and find a robust, positive link between financial intermediation and GDP growth. Jayaratne and Strahan (1996) find that following the U.S. intrastate branch reform in 1970s, per capital growth in income and output increases, mainly due to the improvements in the quality of bank lending. A number of articles find that relaxing restrictions on bank expansion promotes the level of entrepreneurship and small businesses (Black and Strahan, 2002; Cetorelli and Strahan, 2006; Kerr and Nanda, 2009). Burgess and Pande (2005) explore a branch opening policy in Indian, and find that branch expansion program significantly increased non-agricultural output and lowered rural poverty. Burgess, Pande and Wong (2005) provide evidence that the Indian social banking program increased lending to the poor. Cole (2009) examines the effect of bank ownership and finds that government ownership initially increased the quantity, but substantially lowered the quality of financial intermediation. Nguyen (2016) provides evidence that bank branch closings result in a persistent decline in local small business lending. Relatedly, many studies investigate the impact of micro finance programs by exploring randomized control trials and quasi natural experiments (Pitt and Khandker, 1998; Karlan and Zinman, 2009; Kaboski and Townsend, 2011, 2012; Banerjee and Duflo, 2014; Banerjee et al., 2015; Attanasio et al., 2015; Augsburg et al., 2015; Crepon et al., 2015; Tarozzi, Desai and Johnson, 2015).

Our paper highlights several channels identified in the aforementioned literature but in a unified framework, which allows us to interpret and compare the relative quantitative implications of different financial reforms. From a methodological perspective, our paper is closely related to the macro-development literature applying micro-founded general equilibrium models to study growth, inequality, and financial sector policies (see Townsend, 2010, for a survey). The models developed in this literature are built on the theoretical framework of Greenwood and Jovanovic (1990), Banerjee and Newman (1993), and Lloyd-Ellis and Bernhardt (2000) among others. For example, Buera and Shin (2013) quantitatively analyze the consequence of a large-scale economic reform, uncovering the role of financial frictions in explaining the common feature of post-reform transitional dynamics of investment rates and TFP in China, Japan, Korean, Malaysia, Singapore, Taiwan, and Thailand.3

These models explicitly incorporate heterogeneity to capture realistic wealth and firm size distributions. However, none consider the differential financial development by geography, which could be important to understand inter-regional capital and labor flows and the differential development of regions (Moll, Townsend and Zhorin, 2016). By contrast, a large literature in industrial organization

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2Joseph Schumpeter argued that the financial sector influences economic growth by affecting the allocation of savings and not necessarily by changing the rate of savings. A large development economics literature argues that highly developed financial markets promote growth primarily by raising domestic savings rates and attracting foreign capital (see discussions in King and Levine, 1994; Fry, 1995; Bandiera et al., 2000; Easterly and Levine, 2002)

3Other papers in this literature include the work of Gine and Townsend (2004); Cagetti and Nardi (2006); Townsend and Ueda (2006); Jeong and Townsend (2008); Townsend and Ueda (2010); Amaral and Quintin (2010); Buera, Kaboski and Shin (2011); Greenwood, Sanchez and Wang (2010, 2013); Dabla-Norris et al. (2015)
focuses on spatial competition and builds models with local markets and geographic units. However, the models built in this literature either focus on demand side, e.g., elasticity of demand for products, or supply side, e.g., where to locate stores and firms, but none of them compute the full general equilibrium or analyze the aggregate implications of economic policies. For example, Seim (2006) studies a model for location choices in the video retail industry. Jia (2008); Holmes (2011); Ellickson, Houghton and Timmins (2013); Zheng (2016) study competition and entries in the discount retailing industry with a large number of markets. Ho and Ishii (2011) build a spatial model of retail banking and estimate the cross-price elasticities between bank branches opened in different locations. Aguirregabiria, Clark and Wang (2016) study the role of geographic deposit risk diversification in branch location decisions following the 1994 Riegle-Neal Act. A number of other studies take the firms’ locations as given and focus on price/quantity competition, and how elasticities are related to distance (Pinkse, Slade and Brett, 2002; Smith, 2004; Davis, 2006; Houde, 2012).

Our paper introduces local spatial markets and so we go from the spatial competition literature to a macro general equilibrium model. Our goal is to understand the spatial, distributional implications of financial reforms as well as a micro-founded model of growth. The closest work to ours is from Felkner and Townsend (2011) who develop an equilibrium model with spatial heterogeneity. However, their model does not explicitly consider local markets in a network, instead they incorporate reduced-form geographic variations and take financial deepening as exogenously given.4

1.2 An Executive Summary of the Paper with Findings

The paper begins by documenting the spatial patterns in credit access conditions and cash holdings. In 1986, before the financial reforms took impact in Thailand, there was a large variation in credit access conditions across geographic areas. The area around Bangkok and its south and north along the central developed corridor has more commercial bank branches compared to other places. Not surprisingly, these places also have better credit access as a larger fraction of households take bank loans. Moreover, we find suggesting evidence that households living farther away from bank branches tend to hold more cash. The demand for cash is likely motivated to fulfill transactions as for our interested period 1986-1996, most of consumption purchases were in cash while credit card purchases were virtually inexistent.

Motivated by these spatial correlations, we develop a dynamic spatial equilibrium model to rationalize the data and to evaluate the financial reform policies happened during 1986-1996 in Thailand. We

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4Spatial equilibrium models have also been built in development and international trade literature to analyze trade, migration, enterprise development, and growth, etc. A first generation of models on agglomeration and growth tend to have a small number of locations (typically two), which are basically dynamic extensions of economic geography models (see Baldwin and Martin, 2004, for a survey). However, these models focus on a small number of locations, thus restricting the ability of capturing the richness of the observed economic activity distribution in the data. Recently, there are quantitative papers which introduce the trade structure of Eaton and Kortum (2002) to spatial equilibrium models to explain the geography of development. For example, Morten and Oliveiral (2014) develop a spatial equilibrium model based on Moretti (2011) and quantify the general equilibrium impact of access to roads on migration rates and welfare. Desmet, Nagy and Rossi-Hansberg (2015) develop a dynamic version of the spatial equilibrium as in Allen and Arkolakis (2014) to quantify the gains from relaxing migration restrictions of the world economy. These models, however, do not consider heterogeneous agents in local markets/regions. In our model, there are heterogeneous agents living in heterogeneous markets, which allows us to investigate not only across-market welfare implications, but also within market welfare implications, i.e., between entrepreneurs and workers, and their spatial correlations.
consider two major financial sector policies—capital account liberalization and bank expansion, and take their paths as given when calibrating policy shift parameters. As a consequence of capital account liberalization, there was a surge in capital inflows and a decrease in interest rate spread between the prime lending rate and the deposit rate. As a consequence of the banking sector reform, both commercial banks and BAAC (Bank for Agriculture and Agricultural Cooperatives) rapidly expand their operation network, doubling the number of branches during this period.

A defining feature of our model is having spatially connected local markets and differential financial frictions. Market locations are realistically obtained using the Geographic Information System (GIS) from the location of commercial bank branches in 2011, which generally correspond to the intersections of major highways and the locations of major cities. The distance between each pair of markets is measured by the car travel time from a detailed road network. Markets are the places where commercial banks and BAAC open branches. Therefore, depending on the location of branches, financial service costs vary among agents living in different markets.

In each market, there is a continuum of agents who are different from each other in terms of wealth and talent. Agents are infinitely lived and experience alternating periods of working and leisure. In the working period, agents can freely choose from among three occupations: subsisters, workers, and entrepreneurs. Subsisters receive subsistence income, which can be considered as a reservation wage of working. Workers supply labor and receive the equilibrium wage. Entrepreneurs hire workers and install capital to produce. Each agent has access to a production technology whose productivity depends on talent. Since occupations are chosen to maximize income, in the absence of wealth constraints, talented agents choose to be entrepreneurs and less talented agents supply labor or live as subsisters.

Wealth constraints influence occupation choice because the credit market is imperfect. Motivated by the data, we introduce three types of financial frictions. First, agents have to pay an entry cost in order to obtain credit from banks. We assume that the entry cost increases with the travel time to bank branches to capture the large spatial variation in credit access conditions. Second, agents face collateral constraints in borrowing because the usual contractual form of commercial bank loans in Thailand is collateralized debt. Third, we introduce an interest rate spread between the deposit and lending rate to reflect any sort of intermediation costs. The interest rate spread decreases over time exogenously to match the data, which is part of the consequence of capital account liberalization.

Income accrued during the working period along with the initial wealth is transferred to the leisure period. In the leisure period, agents derive utility from consumption, and the wealth not consumed is transferred to the next working period. The consumption and savings decisions are made to maximize expected life-time utility. We assume that agents have to use cash to purchase consumption goods. Holding cash is costly due to the opportunity cost of foregone interests. However, there is an incentive to hold more cash to economize on the transaction fees because every cash withdrawal requires agents to travel to some bank branches. Motivated by the spatial variation in cash holdings, we assume that the transaction fees increase with the travel time to bank branches. As a result, agents living farther away from bank branches would hold more cash and this relationship is disciplined by the data.

To obtain stationary results, we assume that there are two cohorts of equal measures. In any period, one cohort is working and the other is enjoying leisure. The equilibrium interest rate and
wage are determined to clear the capital and labor market. Specifically, the demand for capital from working-period entrepreneurs is equalized to the supply of capital, which is contributed by the wealth of working-period workers/subsisters, the deposit from leisure-period agents, and international capital flows. The demand for labor from working-period entrepreneurs is equal to the supply of labor from working-period workers.

Our model focuses on the branch opening decisions of commercial banks both because their dominant role in the Thai financial system and because their branching strategy is likely to be driven by market incentive. Specifically, we assume that commercial banks act as a cartel and choose where to open new branches. The branching choice is made to maximize discounted profit taken as given the number of branches opened in each year from the data and the exogenous locations of BAAC branches. Banks make profit from the markup (i.e., interest rate spread) over the deposit rate on the financial resources channeled to entrepreneurs. BAAC and commercial banks provide the same credit and withdrawal services to agents at the same costs. For markets with both BAAC and commercial bank branches, we assume that they have equal market share of deposit. Therefore, the exogenous BAAC branch locations influence commercial banks’ branching choice by affecting their profit but there is no strategic interaction between commercial banks and BAAC.

A major obstacle to our quantitative analysis is computing the dynamic spatial equilibrium. Computation is challenging because it requires solving a combinatorial programming problem to obtain optimal branching choice. The problem is particularly difficult to solve in the current setting, given the large decision space of branching choice. To our knowledge, there is no numerical algorithm that solves our model in polynomial time. Many papers in the spatial competition literature also face a similar problem when estimating a model with discrete location choices. A revealed preference approach developed by Pakes et al. (2015) is typically used to obtain a set of moment inequalities for parameter identification (Jia, 2008; Holmes, 2011; Ellickson, Houghton and Timmins, 2013; Aguirregabiria, Clark and Wang, 2016). This estimation procedure is very tractable because it avoids solving equilibria, i.e., the optimal choice of locations. However, this approach does not apply to our analysis because our goal is to predict the expansion of bank branches and analyze the equilibrium outcomes resulting from different financial reforms.

We therefore approximate the equilibrium by developing a new algorithm. Our approximation algorithm considers a sequential branch opening problem and specifies the agent’s savings directly in the utility function (Lloyd-Ellis and Bernhardt, 2000), which is assumed to be Cobb-Douglas. These closed-form savings rates are then calibrated to match the savings rates that would be chosen by forward-looking agents conditional on the same equilibrium transition path. On the bank supply side, we assume that location is opened one by one to maximize current profit internalizing the potential equilibrium effect on prices and aggregate savings. After solving the equilibrium, we check that the branches opened based on this approximation are close to the exact solutions at the provincial level (see Appendix D).

On the agent side, we proceed to solve the savings rates in three stages. In the first stage, we assume

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5 Assuncao, Mityakovy and Townsend (2012) provide evidence that BAAC and commercial banks presumably target different markets in Thailand. BAAC tends to open branches in rural regions to maximize financial access ratio, while commercial banks open branches in wealthy and populous regions to maximize profit. Relatedly, Sapienza (2004) provides evidence that lending from public-sector banks tend to have lower interest rates and target poorer areas.
that every agent has the same weight on savings in the Cobb-Douglas utility function. We solve the equilibrium and calibrate the model parameters using pre intervention data. In the second stage, we allow agents to have different weights on savings, as a function of wealth, talent, and travel time to branches. We calibrate these weights to match the savings rates that would be chosen by forward-looking agents in a steady-state economy based on a guess of branch locations and prices. The equilibrium branch locations and average prices from the first stage are taken as an informative initial guess. We then calibrate and solve the equilibrium branch locations and prices, and iterate multiple times until the guessed branch locations and prices converge to the equilibrium branch locations and the average equilibrium prices. In the third stage, we allow agents to have time-varying, market-specific weights on savings, as a function of wealth and talent. We calibrate these weights to match the savings rates that would be chosen by forward-looking agents in each period based on a guessed path of branch locations and prices along the transition between 1986-1996. The equilibrium path of branch locations and prices from the second stage are taken as an informative initial guess. We then calibrate and solve the equilibrium path of branch locations and prices, and iterate multiple times until the guessed path converges to the equilibrium transition path.

The reason the algorithm has three stages is for implementation purposes. Forming an informative guess of the equilibrium branch locations is difficult because of the large decision space.\(^6\) It turns out that using the equilibrium branch locations from the previous stage gives a very reliable initial guess that accelerates convergence. Although our agents are “myopic” in the sense of utility being a function of savings, the equilibrium obtained from the third stage coincides with the equilibrium of forward-looking agents. This is because we are exactly matching the savings rates with those of forward-looking agents along the entire transition path by imposing state-dependent weights on savings, which shares the spirit of the algorithm implemented by Buera and Shin (2013).\(^7\)

The model is validated at both the macro and micro level: First, the model can correctly predict most of the bank locations opened by 1996. Second, the model captures a certain amount of spatial variation in entrepreneurship and credit access conditions in 1996. Third, the model can generate macro dynamics consistent with the data over the period 1986-1996, including GDP growth, income inequality, and credit access conditions.

We then use the model to quantify the effect of two financial sector reforms. Our simulation results indicate that both capital account liberalization and bank expansion contribute to GDP growth but they have opposite implications on income inequality, which jointly shapes the Kuznets curve. Among the 67% of cumulative GDP growth generated by the model, 33% is attributed to capital account liberalization and 25% is attributed to bank expansion.

The two financial reforms increase GDP through different channels. Capital account liberalization promotes capital deepening. On the one hand, the influx of international capital flows increases the supply of capital. On the other hand, the reduction in the interest rate spread reduces the cost of capital. Both motivate entrepreneurs to invest more, increasing capital intensity. Since entrepreneurs on average

\(^6\)For example, with 1428 markets in our model, the number of possible guesses is \(2^{1428}\).

\(^7\)One drawback of this algorithm is that weights on savings that match savings rates of forward-looking agents could change when evaluating counterfactual policies because the counterfactual equilibrium has different paths of branch locations and prices. But we can readjust the savings rates in counterfactual simulations.
have more income than others, increasing their income further leads to higher inequality.

Bank expansion reduces the credit entry cost and the transaction fee. The former constitutes a credit provision channel which promotes GDP growth by allocating capital more efficiently to more talented entrepreneurs; the latter constitutes a deposit mobilization channel which lowers the demand for cash and increases capital base.\(^8\) We find that credit provision contributes to 17% cumulative GDP growth, larger than the 12% contribution of deposit mobilization. In fact, the relative significance of the two channels depends crucially on the parameters governing the initial financial frictions. That is, the large credit access inequality in 1986 and the small spatial variation in cash holdings imply that the credit channel is relatively stronger compared to the deposit mobilization channel. As a result, income inequality decreases because the dominating credit channel enables relatively poorer agents to obtain credit and earn higher income.

In terms of welfare, bank expansion primarily increases the consumption of agents who were previously excluded from financial intermediation. These agents usually live farther away from bank branches in 1986. By contrast, capital account liberalization mainly benefits agents living closer to bank branches in 1986. This is because agents without credit access do not directly benefit from a larger capital base.

The welfare gains of workers and entrepreneurs are also different. On average, entrepreneurs benefit more from these financial reforms than workers. Bank expansion particularly benefits workers, whose consumption increases by 20%-60% depending on where they live, as opposed to 4.5%-6.5% from capital account liberalization. By contrast, capital account liberalization increases entrepreneurs’ consumption by about 260%-380%, as opposed to 80%-260% from bank expansion. There is an interesting spatial correlation between workers’ and entrepreneurs’ consumption gains. As a consequence of bank expansion, both workers and entrepreneurs are associated with larger increase in consumption if they live farther away from bank branches in 1986. However, in these markets, capital account liberalization results in larger consumption gains for workers but lower consumption gains for entrepreneurs.

2 Data

We conduct our study based on several household surveys and high-quality digital spatial data, precisely rectified in Geographic Information System (GIS). Below we briefly introduce the data.

2.1 Household Surveys and Census Data

The Thai Socio-Economic Survey (SES) is a nationally representative household-level repeated cross-sectional survey conducted by the National Statistical Office (NSO) in Thailand. The first survey was conducted in 1957. Surveys were conducted every five years before 1987, and bi-annually thereafter. SES adopts a clustered random sample stratified by geographic regions over the whole country.

\(^8\)As reviewed by Levine (2005), among other functions, two important ways through which finance promotes growth is by mobilizing deposit and providing credit. Deposit mobilization increases the supply of capital and credit provision directs capital to its best use (Goldsmith, 1969; McKinnon, 1973; Shaw, 1973). Rice and Strahan (2010) provide evidence that relaxed branching restrictions increase credit supply. Egana, Hortacsu and Matvos (2016) estimate the elasticity of insured and uninsured deposits to bank distress.
SES is the only household-level nationally representative survey used in our study. We use the data variable on households’ income to construct the national credit access ratio and the annual wage growth rate of workers. We use the data variable on household occupation to construct the fraction of households engaging in entrepreneurial activities.

The Thai Community Development Department (CDD) dataset is a bi-annual census at the village-level collected by the Rural Development Committee (RDC). The data are collected in two steps. In the first step, members of the RDC fill in the questionnaire by themselves using the existing data from the Tambon office. After that, for each village, a meeting with the village headman and village committee is held and the missing information is collected.

CDD provides data for all villages in Thailand, and is used to construct variables characterizing the spatial variation. We use the data variable on occupation to construct the spatial variation in entrepreneurship, and the data variable on credit access conditions to construct the spatial variation in bank credit (and credit access inequality). We combine the data variable on village population with the municipal population obtained from the Thai Population and Housing Census (PHC) to construct the spatial variation in population. We use the data variables on various assets to construct a wealth index used in estimating the spatial wealth distribution in 1986.

The Townsend Thai Survey dataset provides both annual and monthly panels, in addition to the collection of environmental data. The initial annual survey was conducted in 1997, covering 192 villages in the 48 tambons of the four changwats. The monthly surveys were conducted in 16 villages and 4 amphoes. In each village, 40 households are surveyed starting from August, 1998.

Townsend Thai Survey provides household balance sheet information. We use monthly surveys to construct the cash-to-wealth ratio and loan-to-collateral ratio. We use the 1997 annual survey to construct an indicator for occupation persistence.

The Thai Population and Housing Census (PHC) is conducted every decade and contains population and household records with information on whether the respondents are living in municipal or non-municipal area, and their home province, amphoe and tambon code.

We use the data from PHC to estimate the municipal population of each municipal district, which is combined with village population from CDD to construct market size and the spatial variation in population.

The Enterprise Survey of Thailand is a firm-level survey of a representative sample of an economy’s private sector conducted by the World Bank in 2006. The survey covers 1043 business firms with a broad range of business environment topics being interviewed, including access to finance, corruption, infrastructure, crime, competition, and performance measures.

We use the enterprise survey of Thailand to calibrate the firm employment distribution.
2.2 High-Resolution Spatial Data

We use high-resolution spatial data on bank locations, digitized major and minor road networks, and political boundaries at different administrative levels.

**Road Network** is constructed using the GIS data on Thailand’s transportation system from Thailand Environment Institute. The data provide spatial geometries of nation-wide road, railroad, future segments and intersections.

We use ArcGIS Network Analyst tool to build the Thailand transportation network after excluding railroad and future road segments. In total, 59238 junctures are connected by 7 types of road. We estimate the average vehicle speed for each type of road based on real time information (see Appendix A). Then we estimate the car travel time for all road segments based on road type and the estimated vehicle speed.

**Branch Locations** are constructed using data from the Bank of Thailand, the Bank of Agricultural and Agricultural Cooperative, the Telephone Authority of Thailand, the Community Development Center, and several non-traditional financial institutes.

We merge these data to one central table which includes all bank branches’ opening dates, closing dates (if ever closed), bank name, branch name, etc. We then pinpoint branch locations in each year using Google map API (see Appendix A).

3 Motivating Facts

In this section, we present several facts in Thailand between 1986-1996 to motivate our study. Subsection 3.1 presents the financial liberalization policies initiated during this period, which liberated capital account and resulted in rapid bank expansion. These policy shifts are taken as exogenously given in our quantitative analysis. Subsection 3.2 offers suggesting evidence on the correlation between cash holdings and the travel time to the nearest bank branch, and the spatial correlation between credit access conditions and bank branch locations. These facts motivate us to develop a spatial equilibrium model featuring geographically differential costs in financial transactions and credit entry barriers.


Between 1986-1996, the Thailand’s economy underwent deep structural changes, including the liberalization of its financial sector and the economic integration with global financial and product markets. Since the late 1980s, a series of financial liberalization policies were rapidly adopted. These reform policies were intended to develop a highly functional financial system with efficient financial institutions through the market mechanism. The increased competition surrounding commercial banks could be recognized from the movements of deposit and lending rates. Before the financial liberalization policies adopted in the late 1980s, the prime lending rate to small and medium sized companies differed substantially from the commercial bank’s deposit rate. The interest rate spread, measured as the difference between the

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prime lending rate and the deposit rate, decreased from about 8% in 1986 to about 2% by the end of 1995 (see panel A of Figure 1).

The Thai government also enacted policies to further open the capital account in the late 1980s and early 1990s. As reviewed in Alba, Hernandez and Klingebiel (1999), during 1986 the tax impediments to portfolio inflows were reduced, in particular for purchasing Thai mutual funds. The most important policy was the aim of fostering the development of Bangkok as a regional financial center by establishing the Bangkok International Banking Facility (BIBF) as an offshore financial market with the benefits from tax and regulatory advantages. This capital account liberalization resulted in a surge in private capital flows and rapid credit growth. Between 1988-1996, Thailand is one of the countries that received the largest capital inflows relative to GDP. As shown in panel B, there were visibly no net capital inflows before 1986. The private capital inflows in Thailand surged in 1988, and increased to some US $11 billion (13% of GDP) in 1990, where they stabilized until 1993. The capital inflows surged once again between 1994-1995, surpassing US $21 billion, but declined sharply in 1996 and thereafter due to the financial crisis.

On the other hand, financial policies lead to the expansion of business operations of banks. As of 1987, Thailand’s formal financial system consisted of commercial banks, finance companies, credit financier companies, government savings banks, private and government insurance companies, and a number of sectorally and functionally specialized financial institutions. The central players in the Thai financial system are commercial banks which absorb 80.9% of deposits and account for 73.1% of total financial system assets. The second largest players are specialized government banks, known as Bank for Agriculture and Agricultural Cooperatives (BAAC), capturing 9.5% of total financial system deposits and 14.2% of total financial system assets.

The competitive market environment created after financial liberalization gave the financial institutions strong incentives to expand their business operations. Panel C presents the number of branches operated by commercial banks and BAAC in different locations over the period 1981-1996. The number of commercial bank branches was steadily increasing since the late 80s, and was more than doubled by the end of 1996. Importantly, a substantial number of branches were opened in different locations to explore underdeveloped areas. Compared with the expansion of commercial banks, BAAC opened fewer branches during this period. The expansion of bank branch network played an important role in improving the allocative efficiency of capital among entrepreneurs by equalizing access to credit. As documented by Abiad, Oomes and Ueda (2008), the decrease in the dispersion of Tobin’s Q indicates that there were substantial improvements in allocating capital in Thailand dating from 1987. On the other hand, the expansion of branch network mobilized savings as shown in the next subsection.

In our quantitative analysis, we take these policy shifts as given and our goal is to quantify the distinct roles played by different policies on growth, inequality, welfare, and credit access conditions through the length of a structural model.

### 3.2 Credit Access Conditions, Cash Holdings, and Bank Branch Locations

One of the major roles played by banks is to channel financial resources from households to entrepreneurs. We find that credit access conditions vary dramatically across different regions. The Gini measure of
credit access inequality in 1986 is about 0.5. More importantly, there is a significant positive correlation between credit access conditions and bank branch locations (see Figure 2). In areas where commercial banks opened more branches, the fraction of households with access to credit is also higher. These include large areas around the Bangkok metropolitan area and south and north of this area along the central developed corridor of Thailand. By contrast, in the eastern and southern parts of the country, there are less bank branches and poorer credit access conditions. This is reasonable since in Thailand, people living in villages travel to branches to obtain credit or are served by field officers. In either way, this suggests that the cost of credit provision is negatively correlated with the travel time to the nearest bank branch.

For the period 1986-1996 we study in Thailand, small stores in villages usually only accept cash. As documented by Alvarez, Pawsutipaisit and Townsend (2011), 78.5% of consumption purchases are in cash while credit card purchases are virtually inexistent for Thai households in 1999. This suggests that households have large demand for cash, thus the tradeoff emphasized by Baumol (1952) and Tobin (1956) could play an important role in determining cash holdings. In particular, households should hold more cash when the interest rate is low and when the financial transaction cost is high.

Figure 3 provides some suggesting evidence. Immediately after the Thai financial crisis in 1997-1998, the deposit interest rate decreased from 10.6% to 2.0% in five years. This is accompanied by a sharp increase in households’ cash holdings, from 17% to 38% (see panel A). In panel B, we show that the cash to wealth ratio is positively correlated with the travel time to the nearest bank branch at the 1% level of significance, using the created variables of household cash holdings and wealth from the Townsend Thai monthly surveys during the period 1998-2011. This correlation seems to imply that households living in villages distant from bank branches were incurring larger transaction costs, which could be considered as some “shoe-leather” costs.\(^9\)

### 4 Quantitative Model

The spatial correlations between credit access conditions, cash holding, and bank locations motivate us to develop a spatial equilibrium model incorporating differential costs in financial transactions and credit entry barriers in different geographical areas. In this section, we build such a model to rationalize the data and to evaluate the financial reform policies happened during 1986-1996 in Thailand.

#### 4.1 Environment

Time is discrete and denoted by \(t\). The economy consists of \(N\) markets, which are connected to each other through road networks. In each market \(n\), there lives a continuum of agents, whose measure (i.e., market size) is constant over time and denoted as \(P^n\).\(^{10}\)

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\(^9\)Figure 3 also indicate that households living in these villages hold 20%-25% of their wealth in cash, which are much larger than those in industrialized countries. Explaining the high level of cash holdings in Thailand is beyond the goal of this paper.

\(^{10}\)In the data, the Thai population increased by about 20% during 1986-1996, but the relative market-level population among the markets we defined was virtually unchanged. This means that assuming constant population is innocuous, since neither the simulated strategy of bank expansion nor the macroeconomic statistic (i.e., GDP per capita, income inequality, credit access ratio and inequality) generated by our model is affected by the overall level of population.
There are two kinds of bank branches, opened by commercial banks or BAAC, which provide exactly the same financial services at the same cost. Each market may have no branch, or one branch from commercial banks or BAAC, or both.

4.1.1 Definition of Market

There are 1426 markets, whose locations are geo-proximated by the locations with one or more commercial bank branches opened by 2011. We map BAAC branches to their nearest commercial bank locations.\textsuperscript{11} In particular, using Google map API, we obtain the village/tambon/municipal name of each commercial bank branch location. For those branches that can be matched directly to any village, the village’s location, which is represented as point data in the GIS system, is used to proxy the branch’s location. Branches that cannot be matched at the village level are matched to tambons and/or municipal districts (both are geo-units represented as polygon areas in the GIS system). They are assigned to road network intersections according to the procedures elaborated in Appendix A. In 1986, there are 406 markets with commercial bank branches and 343 markets with BAAC branches, among which 171 markets have both commercial bank branches and BAAC branches. The 1020 markets without commercial bank branches in 1986 are the places where commercial banks can open branches looking forward. As we describe in subsection 4.3, given the observed number of new commercial bank branches opened in each year, we allow the bank to choose where to open these branches. Between 1986-1996, 437 commercial bank branches are opened and there are 589 markets without commercial bank branches by 1996.

Figure 4 illustrates the market segmentation and the GIS data in province Buriram. In this province, there are 17 markets with their borders depicted by blue lines. The blue dots represent commercial bank branch locations. In each market, there is a single bank location. The border of the market is determined such that any point inside the market border has the minimum travel time to the bank location within the market relative to other bank locations. Note that the travel time is measured from the road network (the grey solid line), thus it is possible that the Euclidean distance between a point and the bank location in other markets appears shorter on the map. The color of each market represents the market size, estimated to reflect village and municipal population (see below for its estimation).

Agents living in different markets receive financial services (i.e. saving and borrowing elaborated in subsection 4.2) at the nearest bank branch, thus may possibly incur differential transaction costs depending on the spatial distribution of branches. Consider an agent who lives within a market with at least one branch. The travel time from the agent’s location to the bank location can be measured from the road network. For tractability, we assume that the travel time within each market is zero, which is equivalent to assuming that all agents are living exactly at the bank location in each market.\textsuperscript{12} If the agent lives in a market without a bank branch, then she needs to travel to nearby markets to receive

\textsuperscript{11}Our paper focuses on predicting the expansion of commercial banks due to its dominating role in Thai financial system. Therefore, we only consider locations with commercial bank branches when constructing markets, while ignoring the locations with only BAAC branches.

\textsuperscript{12}In principle we can calculate the travel time between villages and the bank location in each market since the village locations are available in the data. However, running the model at the village level requires substantially more computation power as there are about 70,000 villages in Thailand.
financial services. The travel time in this case, is measured by the travel time between the bank location of the market where the agent lives in and the bank location of the market where she receives financial services.

Therefore, essentially our model economy is an abstraction of the real economy with a network of 1426 nodes representing 1426 markets, which are connected by roads (see panel B of Figure 4 for an illustration).

4.1.2 Market Size

We use municipal and village population to proxy the market size $P_n$. Given the distribution of agents’ characteristics, the market size can be considered as a scale factor which proportionately affects bank branches’ intermediation profit. We estimate the population of each market using the data on village population from CDD and the data on municipal population from PHC in 1990.\(^\text{13}\)

To elaborate, we assign each village’s population to its nearest market, as measured by the travel time between the village and the market location. The village population associated with any market is obtained by adding up all the assigned village population. The estimation of municipal population is more involved, since municipal districts are represented as polygon areas in the GIS system.\(^\text{14}\) We use the following rule to assign municipal population to markets: For any municipal district, if there are markets located within it, its municipal population is evenly assigned to these markets. Otherwise, its municipal population is assigned to the nearest market, as measured by the travel time between the municipal’s geometric center and the market location.

The market size $P_n$ is estimated to be the sum of village and municipal population in market $n$. We validate that the difference between the estimated market population and the census data is within 5% at both national and provincial levels. Figure 5 presents the estimated market-level population density, showing that regions around Bankok and in the western part of country are more populous. This indicates that our estimation of population density at the market-level disaggregation is able to capture the population density variation in Thailand.

4.2 Agents

Agents are living indefinitely and there are alternating periods of working and leisure. During working periods, agents choose occupations and supply labor to obtain income. During leisure periods, agents enjoy consumption.\(^\text{15}\)

\(^{13}\)We consider the year 1990 since this is the only year in which both surveys were conducted. The CDD survey was conducted bi-annually between 1986-1996, and between 1999-2011. The PHC survey was conducted every decade, in 1990, 2000, and 2010, respectively.

\(^{14}\)An intermediate step is taken to estimate municipal population for each municipal district. PHC records whether a specific respondent lives in municipal or rural community, but provides no information on the specific municipal district. The location code system allows us to know which amphoe the record is belonged to, thus we estimate the municipal population for each municipal district using the following approximation rule. For municipal districts located within amphoe with a single municipal district, the population of the municipal district is estimated to be the municipal population of the amphoe. For municipal districts located in amphoe with more than one municipal districts, the population of each municipal district is estimated to be proportional to its area.

\(^{15}\)The approach of working and leisure dichotomy enables us to capture the endogenous occupation choices and cash holdings in a tractable way without specifically modeling the flow of income. Similar approaches have been adopted by other
In our economy, there are two cohorts of agents of equal measures: One cohort of agents lives in "working period" in period \( t \), and "leisure period" in period \( t + 1 \), and "working period" in period \( t + 2 \), ..., and so on. The other cohort of agents lives in "leisure period" in period \( t \), and "working period" in period \( t + 1 \), ..., and so on. Below we describe the behavior of agents belonged to the former cohort, and the latter cohort’s behavior is symmetric.

Agents are distinguished from each other in wealth \( b_t \) and talent \( z_t \). The wealth \( b_t \) evolves endogenously, determined by agents’ optimal decisions described below. The talent \( z_t \) captures individual characteristics (e.g., human capital and skills, etc) that determine entrepreneurial productivity. It is realized at the beginning of the working period and remains constant until the beginning of the next working period, i.e., \( z_{t+1} = z_t \). We assume that \( z_t \) follows a Markov process: with probability \( \gamma \), \( z_t \) is drawn from an invariant Pareto distribution \( \Gamma(z) \) with tail parameter \( \rho \); with probability \( 1 - \gamma \), \( z_t \) is equal to \( z_{t-2} \), which is the talent realized in the previous draw. The shock to talent can be interpreted as changes in market conditions that affect the profitability of agents’ skills (Buera and Shin, 2013). We calibrate parameter \( \rho \) to match the firm employment distribution. Parameter \( \gamma \) is identified from the frequency of occupation changes.

The initial household wealth distribution in 1986 is estimated using village wealth index. The CDD dataset does not record total wealth data, but it does record various wealth items. With information on these wealth items, we proxy the wealth index using the first principal component vector of three durable assets, including per capita TV ownership per village, per capita motorcycles per village, and per capita pickup vehicles per village. The first principle component best summarizes the variation in the ownership of the three major wealth items across villages. The limited number of villages restricts us from recovering the exact wealth distribution for each market.\(^{16}\) Therefore, we calibrate the mean wealth index for each market to capture the cross-market wealth dispersion and approximate the within-market wealth dispersion across households using the wealth distribution at the national level.

In particular, we proceed the calibration of market-level wealth distributions in three steps. First, we fit the histogram of all 19519 villages’ wealth index using a double exponential function to estimate the national wealth distribution in Thailand, denoted as \( \Psi_0(b) \) (see the solid curve in Figure 6). Then, we assign these villages to their nearest markets, and calculate the mean wealth index for each market, denoted as \( \bar{b}_n \). Finally, we calibrate the wealth distribution in each market \( n \) by normalizing the national wealth distribution with the market-level mean wealth index, i.e., \( \Psi_n(b) = \frac{\int_{b}^{\infty} b \Psi_0(b) \, db}{\int_{b}^{\infty} \Psi_0(b) \, db} \Psi_0(b) \) (for example, see the dashed curve in Figure 6). Therefore, the estimated market-level mean wealth index can be considered as a scale factor that tailors the national-level wealth distribution to reflect the cross-market variation in wealth. The estimated initial wealth index captures the fact that areas around Bankok and the central corridor are wealthier relative to other parts of the country (see Figure 7).

In the following, we illustrate the problems of the working period and the leisure period respectively,
and we summarize the timing of events at the end.

### 4.2.1 Working Period—Occupation Choice and Credit Entry

In the working period, upon the realization of the talent shock $z_t$, agents can choose from among three occupations: wage subsistence agriculture, work, or enterprise. To begin, subsisters work in the agricultural sector and earn a subsistence return $f_t$. Workers supply one unit of labor and earn the equilibrium wage $w_t$. The subsistence return $f_t$ is exogenous, calibrated to match the data as we describe below. The wage $w_t$ is determined endogenously by the labor market clearing condition. Entrepreneurs operate businesses locally, employing workers and capital for production. Business profit is realized at the end of the working period.

Entrepreneurs have access to a production technology, whose productivity depends on talent $z_t$. The production function is

$$f(k_t, l_t) = z_t(k_t^{\alpha} l_t^{1-\alpha})^{1-\nu}, \quad (4.1)$$

where $1 - \nu$ is the Lucas span-of-control parameter, representing the share of output going to the variable factors. Out of this, fraction $\alpha$ goes to capital, and $1 - \alpha$ goes to labor. Production exhibits diminishing returns to scale with $\nu > 0$. Capital depreciates by $\delta$ after use. Their parameter values are set according to the estimate of Samphantharak and Townsend (2009) and Paweenawat and Townsend (2014).

We assume that workers and subsisters can migrate costlessly and work anywhere in the economy, thus both $f_t$ and $w_t$ are the same across markets. Location matters, however, for entrepreneurs who may demand bank credit as in Felkner and Townsend (2011). To obtain credit, agents have to incur a credit entry cost $\phi_t$, which parsimoniously captures the lump-sum fee or utility loss from obtaining a loan contract (Greenwood and Jovanovic, 1990).

According to the facts presented in subsection 3.2, the percent of households with credit access is related to the location of bank branches. To capture this, we assume that the credit entry cost increases exponentially with the travel time to the nearest bank branch $d_t$,

$$\phi_t = \exp(\kappa d_t) + \eta. \quad (4.2)$$

For agents who are living in markets with bank branches, $d_t = 0$. Otherwise, $d_t$ is estimated from the travel time along the road network between the market where the agent lives in and the nearest market that contains a branch. The exponential function allows us to capture the large credit access inequality across different markets. Intuitively, the parameter $\kappa$ governs the spatial variation in credit entry costs across different markets and the parameter $\eta$ controls the overall barrier in credit access. Therefore, these two parameters are identified from the credit access inequality and the average credit access ratio in Thailand.

After paying the credit entry cost, agents can borrow from the bank in that period. The bank lending rate is higher than the deposit rate by a markup $\chi_t$, which is calibrated to match the interest rate spread.

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\(^{17}\)As documented by Townsend (2011), in 1976, 30% of population worked as workers, 15% of population owned businesses, and the rest worked in agriculture. In the following years, there was a steady rise in the number of workers and a decline in the number of subsisters.
reflecting any sort of intermediation costs. Moreover, borrowing is restricted by a collateral constraint, $k_t \leq \lambda b_t$.\footnote{In Buera and Shin (2013) and Moll (2014), this constraint is motivated as arising from a limited commitment problem. Agents can abscond with a fraction of $1/\lambda$ of the rented capital. The only punishment is that they will lose their collateral $a$ and the interest earning on it. In equilibrium, agents do not abscond only if the amount of credit is less than $\lambda a$. Therefore, the bank is only willing to lend $\lambda a$ if $a$ units of collateral are posted. In our model, we assume that wealth $b_t$ is used as collateral.} The single parameter $\lambda \geq 1$ parsimoniously captures the degree of financial friction resulting from limited commitment. A special case of $\lambda = 1$ implies that agents cannot borrow. As we state in subsection 3.1, commercial banks play a dominant role in the financial market, whose usual contractual form of loans is collateralized debt. Thus, the collateral constraint introduced here captures the major friction in the financial market. The parameter $\lambda$ is estimated directly to match the 95th percentile of the loan-to-collateral ratio in the micro data on households loans.

Notice that our model features three sources of financial frictions: the credit entry cost, the intermediation cost, and the collateral constraint. The credit entry cost can be considered as a friction on the extensive margin, which governs the credit access ratio, or the proportion of entrepreneurs who obtain bank credit; while the intermediation cost and the collateral constraint work mainly through the intensive margin, determining the amount of credit offered by the bank. The intermediation cost and the collateral constraint, however, can also affect the credit access ratio since providing entrepreneurs with more cheap credit also motivates them to pay the entry cost.

Denote $o_t = 0, 1, 2$ as the occupation choice and $\pi_t$ as the income in period $t$, then

$$
\pi_t = \begin{cases} 
    f_t + r_t b_t, & \text{if } o_t = 0 \text{ (subsisters)}, \\
    w_t + r_t b_t, & \text{if } o_t = 1 \text{ (workers)}, \\
    \mu_t, & \text{if } o_t = 2 \text{ (entrepreneurs)},
\end{cases}
$$

where $r_t$ is the equilibrium deposit rate in period $t$, and $\mu_t$ represents the income of entrepreneurs, as characterized below.

Notice that subsisters and workers co-exist only when $f_t = w_t$. Therefore, the subsistence return $f_t$ can be considered as a reservation wage, below which every potential worker prefers to remain in the subsistence sector. On the other hand, if the equilibrium wage $w_t$ is higher than the subsistence return, no one remains in the subsistence sector. We allow the subsistence income $f_t$ to grow exogenously at the rate $g_f$. As we describe later in section 6, $g_f$ is calibrated to match the wage growth rate in Thailand between 1976-1986, a preceding period during which there are comparable fractions of labor force working as subsisters or workers. As long as subsisters and workers co-exist, the population proportion of workers and subsisters is determined by the entrepreneurs’ demand for labor. Likewise, as the economy develops, the demand for labor may increase to the level beyond which the equilibrium wage becomes higher than the subsistence return. When this happens, subsisters disappear and there are only entrepreneurs and workers. Therefore, entrepreneurs’ demand for labor depends on the cost of labor, which is equal to the subsistence return when workers and subsisters coexist. This suggests that we can identify the initial value of subsistence return, $f_0$, from the fraction of entrepreneurs in 1986, the initial year of our simulation in which both workers and subsisters are existent.

Denote $g_t = 0, 1$ as the credit entry decision, $\mu^c_t$ and $\mu^s_t$ as the income of entrepreneurs with and
without credit, respectively. Entrepreneurs choose to pay the credit entry cost \( \phi_t \) if \( \mu_t^c > \mu_t^s \) thus

\[
\mu_t = \max \{ \mu_t^s, \mu_t^c \}. \tag{4.4}
\]

If entrepreneurs do not borrow, they save the credit entry cost \( \phi_t \) but have to self finance the production. Their income include interest earnings on bank deposit, \( r_t(b_t - k_t) \), and production profit, which are the value of output \( z_t(k_t^{1-a_1})^{1-\nu} \) net of depreciated capital \( \delta k_t \) and labor cost \( w_t l_t \). Hence, entrepreneurs solve

\[
\mu_t^s = \max_{l_t, k_t} z_t(k_t^{1-a_1})^{1-\nu} - \delta k_t - w_t l_t + r_t(b_t - k_t)
\]

subject to \( k_t \leq b_t \). \tag{4.5}

If entrepreneurs choose to borrow, they have to pay the credit entry cost \( \phi_t \) and deposit wealth \( b_t \) in the bank as collateral to obtain credit. The bank charges a markup \( \chi_t \) on the credit provided to entrepreneurs, \( k_t - b_t \), over the deposit rate \( r_t \). Thus entrepreneurs solve

\[
\mu_t^c = \max_{l_t, k_t} z_t(k_t^{1-a_1})^{1-\nu} - (\delta + r_t)k_t - \chi_t \max\{k_t - b_t, 0\} - w_t l_t + r_t b_t - \phi_t
\]

subject to \( k_t \leq \lambda b_t \). \tag{4.6}

The constraints in problems (4.5) and (4.6) capture the maximum amount of capital that can be invested in production for entrepreneurs without or with credit access. Note that since talent shock is realized at the beginning of the working period, the agent knows for sure the amount of entrepreneurial income when making occupation choices.

### 4.2.2 Leisure Period—Consumption, Cash, and Savings

Agents enter the leisure period with wealth \( b_{t+1} = b_t + \pi_t \) in period \( t + 1 \), where \( \pi_t \) is determined by the occupation choice specified in equation (4.3). We assume that income \( \pi_t \) realized in the working period is paid directly to the savings account.\(^{19}\) Therefore, the beginning-of-leisure-period wealth \( b_{t+1} \) is all in the savings account and agents hold no cash when entering the leisure period.

In the leisure period, agents have to decide consumption \( c_{t+1} \), cash holdings \( m_{t+1} \), and savings \( b_{t+2} \). Consumption \( c_{t+1} \) is realized continuously and agents have to use cash to fulfill consumption. As in Baumol (1952) and Tobin (1956), agents face a tradeoff from cash holdings, i.e., interest from time deposit like bond or other forms of financial assets and transaction costs. The realized utility is \( u(c_{t+1}) \) in period \( t + 1 \). Therefore, although we allow continuous consumption to motivate cash demand, utility only depends on the total amount of consumption in the leisure period as opposed to the consumption flow in standard continuous time models.

We assume that transaction costs are only incurred for withdrawals but not for deposits as in Baumol (1952). The tradeoff between transaction costs and cash holding costs (or foregone interests) is made

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\(^{19}\)This assumption is supported by empirical facts in Thailand. For example, Alvarez, Pawaitsuipaisit and Townsend (2011) find that Thai households make both large deposits and withdrawals within the same month, which is puzzling as both deposits and withdrawals incur financial transaction costs (as in Baumol, 1952; Tobin, 1956). The authors show that deposits are made by firms for wage payments after a careful review of the data.
clear as follows. At the beginning of the leisure period, agents can withdraw $c_{t+1}$ from the bank by paying a single transaction fee (denoted by $\zeta_t$) at the cost of foregone interest that would have been earned if $c_{t+1}$ is not all withdrew from the beginning. Alternatively, agents can withdraw multiple times, each with a smaller amount, to save interest earnings but at a cost of paying more transaction fees. In particular, for agents who make $N_{t+1}$ trips to the bank, each time the amount of withdrawal is $\frac{c_{t+1}}{N_{t+1}}$. Thus the average cash holdings are $\frac{r_{t+1} c_{t+1}}{2N_{t+1}}$, and the total cost is equal to the sum of forgone interest $\frac{r_{t+1} c_{t+1}}{2N_{t+1}}$ and transaction costs $N_{t+1} \zeta_{t+1}$.

Given consumption $c_{t+1}$, the optimal number of trips $N_{t+1}$ minimizes the cash management cost,

$$\frac{r_{t+1} c_{t+1}}{2N_{t+1}} + N_{t+1} \zeta_{t+1}. \tag{4.7}$$

This yields the optimal number of trips\(^{21}\):

$$N_{t+1} = \sqrt{\frac{r_{t+1} c_{t+1}}{2\zeta_{t+1}}}. \tag{4.8}$$

Intuitively, equation (4.8) implies that agents prefer to make more trips to the bank when holding cash is relatively more costly, which happens when the interest rate is higher or the transaction fee is lower. The average cash holdings $m_{t+1}$ is derived as a function of consumption $c_{t+1}$,

$$m_{t+1} = \sqrt{\frac{c_{t+1} \zeta_{t+1}}{2r_{t+1}}}, \tag{4.9}$$

which implies that agents’ cash holdings increase with the transaction fee and decrease with the interest rate.

To close the leisure-period problem, we provide a micro foundation for the transaction fee $\zeta_{t+1}$. Baumol (1952) attributes this transaction cost as a “broker fee”, which represents all non-interest costs of making a cash withdrawal. The empirical result presented in Figure 3 motivates us to interpret this cost as a “shoe-leather” cost, which increases with the travel time to the nearest bank branch, as captured by the following function:

$$\zeta_{t+1} = s \log(1 + d_{t+1}). \tag{4.10}$$

Parameter $s$ governs the cost of holding cash and is calibrated to match the average cash-to-wealth ratio. With dynamic bank expansion, the financial transaction cost $\zeta_{t+1}$ is market specific and time varying. Our assumption that agents enter the leisure period with all of their wealth in the savings account implies that agents have to make at least one withdrawal to finance consumption. Concerning the fact that agents living in rural areas might never make any deposits due to the high traveling cost to a bank branch, this assumption may potentially overestimate the quantitative impacts of dynamic\

\(^{20}\)Notice that an agent withdraws only when she is running out of cash since holding cash is costly and consumption is continuous. Moreover, the amount of withdrawal is equally split among the $N_{t+1}$ trips, as one can prove that asymmetric splitting is not optimal.

\(^{21}\)Although more realistic, restricting $N_{t+1}$ to be a positive integer requires us to solve a mixed-integer programming problem, which significantly increases computational complexity. Thus for simplicity, we allow $N_{t+1}$ to be real-valued following Baumol (1952).
bank expansion. To address this concern, we assume that the first withdrawal made by agents living in markets without bank branches does not incur transaction costs. This is equivalent to allowing these agents to freely adjust their cash to deposit ratio at the end of the working period.

4.2.3 Timing and Recursive Formula

The timing of agent’s problem is summarized in Figure 8. At the beginning of the working period, the talent shock $z_t$ is realized and then the agent chooses occupations. If the agent chooses to start a business, she has to choose capital $k_t$, labor $l_t$, and decide whether to obtain credit. Income $\pi_t$ is realized at the end of the working period, after which the agent pays the credit entry cost $\phi_t$ if she borrowed. In the leisure period, the agent chooses consumption $c_{t+1}$ and savings $b_{t+2}$. Given the consumption plan, the agent also has to choose how frequently she visits the bank branch and the amount of cash holding according to equations (4.8) and (4.10).

Denote $V_t(b_t, z_t; n)$ as the value function of the agent of type $(b_t, z_t)$ living in market $n$, immediately after the realization of the talent shock $z_t$ in the working period $t$. The agent solves the following recursive problem

$$V_t(b_t, z_t; n) = \max_{o_t, g_t, N_t+1, c_{t+1}, b_{t+2}} u(c_{t+1}) + \beta^2 [(1 - \gamma)V_{t+2}(b_{t+2}, z_t; n) + \gamma E[V_{t+2}(b_{t+2}, z_{t+2}; n)]]$$

subject to

$$b_{t+1} - b_t = (f_t + r_t b_t)\mathbb{I}_{o_t=0} + (w_t + r_t b_t)\mathbb{I}_{o_t=1} + (\mu_t^f \mathbb{I}_{g_t=0} + \mu_t^r \mathbb{I}_{g_t=1})\mathbb{I}_{o_t=2},$$

$$c_{t+1} + b_{t+2} \leq b_{t+1} + r_{t+1} \left( b_{t+1} - \frac{c_{t+1}}{2} \right) - \frac{r_{t+1} c_{t+1}}{2N_{t+1}} - N_{t+1} \xi_{t+1},$$

$$N_t+1, c_{t+1}, b_{t+2} \geq 0,$$

where $\beta$ is the time discount factor calibrated to match the real interest rate in 1986. The first constraint gives the amount of wealth $b_{t+1}$ at the beginning of the leisure period. The second constraint represents the budget constraint in the leisure period, where the term $r_{t+1} \left( b_{t+1} - \frac{c_{t+1}}{2} \right)$ captures the interest earnings if the agent holds no cash, i.e., $N_{t+1} = \infty$.

4.2.4 The Supply of Labor and Capital

Note that in any period $t$, there are equal measures of agents living in the working period and the leisure period. Among those living in the working period, agents who choose to be entrepreneurs demand labor and capital. The supply of labor is provided by working-period agents who choose to be workers. Moreover, the supply of capital is provided by all agents regardless which period they live in and the international capital inflows, if any (see Table 1). In particular, agents living in the working period have all of their wealth deposited in the bank, hence their contribution to capital supply is equal to their beginning-of-period wealth. Agents living in the leisure period have decreasing deposits over time as consumption is continuously realized and cash is intermittently withdrawn from the savings account. We consider the average amount of deposit held by agents living in the leisure period as their contribution to the supply of capital.
Given consumption $c_{t+1}$, initial wealth $b_{t+1}$, and the number of trips to the bank branch $N_{t+1}$. We know from the above analysis that during each trip agents withdraw $c_{t+1}/N_{t+1}$ from the bank. Therefore, the amount of deposit after the $n$th withdrawal is $b_{t+1} - n c_{t+1}/N_{t+1} - n \zeta_{t+1}$, and the average amount of deposit held in the leisure period is

$$s_{t+1} = \frac{1}{N_{t+1}} \sum_{n=1}^{N_{t+1}} \left[ b_{t+1} - n \left( \frac{c_{t+1}}{N_{t+1}} + \zeta_{t+1} \right) \right]$$

$$= b_{t+1} - \frac{N_{t+1} + 1}{2N_{t+1}} c_{t+1} - \frac{N_{t+1} + 1}{2} \zeta_{t+1}.$$

(4.12)

4.3 The Bank

We focus on commercial banks, and assume that they act jointly as a cartel (hereinafter called the bank). In each period, the bank chooses where to open new branches to maximize discounted profit taking as given BAAC’s branch locations, which are calibrated to match the data. This assumption is to some extent unrealistic since there may possibly exist strategic competition among commercial banks operated by different organizations, and between commercial banks and BAAC. Given the model complexity, however, we could not incorporate the dynamic game played by different types of banks.\(^{22}\)

4.3.1 Profit and Branch Opening

The bank makes profit solely from the interest rate spread, $\chi_{t}$, between the deposit rate and the loan rate. Although the bank’s profit may come from other sources, as documented by Okuda and Mieno (1999), even after the financial reform policies, non-interest income earned from investments in securities and various fee businesses were still less than 10% over the period 1985-1994 in Thailand. We take the interest rate spread $\chi_{t}$ as given and calibrate it from the data (see Table 1).

The equilibrium interest rate is adjusted to clear the capital market. As a result, the total amount of savings plus the amount of capital inflows is always equal to the total amount of loans. Therefore, the bank’s aggregate profit in period $t$, $\Pi_{t}$, is equal to the total amount of savings from all markets and capital inflows from abroad multiplied by the interest rate spread $\chi_{t}$. The amount of savings from

\(^{22}\) Assuncao, Mityakovy and Townsend (2012) find that in Thailand, government development banks and commercial banks have different objective functions. Government development banks prefer to open branches in less populous and more distant locations, while commercial banks tend to open branches in wealthy locations. However, studying their competition for locations is impossible in our large-scale spatial model as the problem solved by Assuncao, Mityakovy and Townsend (2012) is already NP-hard even without heterogeneous agents.
market $n$ is given by:

$$S^n_t = P^n \left[ \int \int \max(b - k^n_t(b, z), 0) h^n_t(b, z) \, db \, dz \right] + \int \int bh^n_t(b, z) \, db \, dz$$

net savings from working-period entrepreneurs

$$+ \int \int s^n_t(b, z) h^n_t(b, z) \, db \, dz$$

savings from working-period workers

savings from leisure-period agents

$$\left( \int \int (b, z) \in E^n_t \max(b - k^n_t(b, z), 0) h^n_t(b, z) \, db \, dz \right) + \left( \int \int bh^n_t(b, z) \, db \, dz \right)$$

(4.13)

where $P^n$ is the market size, $E^n_t$ is the set of working-period entrepreneurs, $s^n_t(b, z)$ is the average amount of savings held by agents of type $(b, z)$ in the leisure period in market $n$, computed from equation (4.12), $h^n_t(b, z)$ are the joint probability density distributions of wealth and talent in market $n$ of the cohort living in the working period and leisure period, respectively. The market-level savings $S^n_t$ is deterministic since there is no aggregate uncertainty.

Savings $S^n_t$ in market $n$ could be deposited in either the bank or BAAC. To elaborate, note that agents living in market $n$ conduct financial transactions in the nearest bank branch, denoted as market $m$ ($m = n$ if market $n$ has a branch). Therefore, the savings $S^n_t$ from market $n$ are saved in branches opened in market $m$. To compute the bank’s savings collected from market $n$, there are three cases: (1). if market $m$ only has a commercial bank branch, then all savings in market $n$ are accrued to the bank. (2). if market $m$ only has a BAAC branch, then none of the savings in market $n$ are accrued to the bank. (3). if market $m$ has both a commercial bank branch and a BAAC branch, then we assume that half of the savings in market $n$ are accrued to the bank. Denote $\Lambda^1$, $\Lambda^2$, and $\Lambda^3$ as the set of markets for case (1), (2) and (3), respectively. The formula for the bank’s total profit in period $t$ is as follows:

$$\Pi_t = \chi_t \left[ \sum_{n \in \Lambda^1} S^n_t + \frac{1}{2} \sum_{n \in \Lambda^3} S^n_t + \text{CAPITAL INFLOW}_t \right],$$

(4.14)

which is equally distributed to all agents at the end of the period.\textsuperscript{23} New branches are opened to maximize discounted profit:

$$\sum_{t=0}^{\infty} \beta^t \Pi_t.$$  

(4.15)

We calibrate the bank’s initial branch locations in 1986, $\Xi_0$, and the number of branch openings in each year, $y_t$, between 1986-1996 to match the data (see Table 1). The way we set up the bank’s branch opening problem implies that there would not be multiple branches opened by commercial banks in the same market. This is because opening a second branch does not change agents’ transaction fees, and hence the bank’s profit remains the same. In the data, we do observe that there are multiple branches opened in the same market. In fact, this inconsistency is caused by the degree of aggregation. The

\textsuperscript{23}Both the profit from commercial banks and the profit from BAAC are equally distributed to all agents in each period. This implies that whether international capital flows into commercial banks or BAAC does not matter for our quantitative results.
problem could be avoided if either we define markets at a finer level or allow markets to occupy a measurable area instead of being modeled as a single point. However, there is a trade-off between computation time and the degree of aggregation.

4.3.2 Illustration of Network Effect

Since all markets are connected with each other, there is a network effect in the bank’s profit when a new branch is opened. After the bank opens a new branch in market $m$, not only the savings in market $m$ but also the savings of agents living in nearby markets who find market $m$ has the closest bank branch will increase. There is also a general equilibrium effect from the change in the interest rate and wage which affects savings in all the markets. Let the variables with top symbol $\sim$ denote the values before the bank setting up the new branch, we formalize the change in savings in the following formula:

$$
\Pi_t - \Pi_t' = \chi t \left[ 1_{m \in \Lambda^1} (S^m_t - \tilde{S}^m_t) + 1_{m \in \Lambda^2 \cap \Lambda^1} S^m_t + 1_{m \in \Lambda^2 \cap \Lambda^3} \frac{1}{2} S^m_t + 1_{m \in \Lambda^1} (S^m_t - \frac{1}{2} \tilde{S}^m_t) \right]
$$

increase in the bank’s savings from agents in market $m$ where the new branch is opened

$$
+ \sum_{n \in \{n : d^n_t < \tilde{d}^n_t \} \cap \Lambda^1, n \neq m} (S^n_t - \tilde{S}^n_t) + \sum_{n \in \{n : d^n_t < \tilde{d}^n_t \} \cap \Lambda^2, n \neq m} S^n_t + \sum_{n \in \{n : d^n_t < \tilde{d}^n_t \} \cap \Lambda^3, n \neq m} (S^n_t - \frac{1}{2} \tilde{S}^n_t)
$$

increase in savings from agents in adjacent markets who come to the new branch

$$
+ \sum_{n \in \{n : d^n_t = \tilde{d}^n_t \} \cap \Lambda^1, n \neq m} (S^n_t - \tilde{S}^n_t) + \sum_{n \in \{n : d^n_t = \tilde{d}^n_t \} \cap \Lambda^2 \cap \Lambda^3, n \neq m} (\frac{1}{2} S^n_t - \tilde{S}^n_t) + \sum_{n \in \{n : d^n_t = \tilde{d}^n_t \} \cap \Lambda^3, n \neq m} (\frac{1}{2} S^n_t - \frac{1}{2} \tilde{S}^n_t)
$$

change in savings from agents in distant markets due to the general equilibrium effect

The second term in equation (4.16) reflects a network effect. It implies that opening a branch in the market that provides the highest profit from this market alone (as captured by the first term in (4.16) may not be the best choice, since the profit from branches in other markets would also be affected. Hence, when the bank chooses the location of new branches, it has to consider the network structure and the spatial distribution of existing branches. New branches should be opened in the markets that maximize the increase in total savings. We discuss the implication of the network effect in subsection 6.2.1.

4.3.3 Two Channels of Bank Expansion

The expansion of bank branches serves the economy through both deposit mobilization and credit provision. On the one hand, opening new branches reduces agents’ cost of obtaining financial services. The reduction in deposit/withdrawn transaction costs enables agents to hold less cash and save more.
This deepens the capital base and thereby more funds can be channeled to entrepreneurs. On the other hand, lower credit entry costs limit the waste of money during credit provision, and enable more entrepreneurs to borrow, which further increases output through capital reallocation. We quantify their respective effects on the dynamics of GDP, inequality, and credit access conditions in subsection 7.2.

4.4 Competitive Equilibrium

Denote \( h_0^n(b,z)_1 \) and \( h_0^n(b,z)_2 \) as the initial joint probability density distribution of wealth and talent in market \( n \) of agents living in the working period and leisure period, respectively. Given an initial distribution of bank branches \( \Xi_0 \), an exogenous sequence of the number of new branches \( \{y_t\}_{t=0}^\infty \) opened in each subsequent period \( t \geq 0 \), and \( h_0^n(b,z)_1 \) and \( h_0^n(b,z)_2 \), a competitive equilibrium consists of allocations \( \{c_t^n(b,z), o_t^n(b,z), g_t^n(b,z), k_t^n(b,z), l_t^n(b,z), N_t^n(b,z), m_t^n(b,z)\}_{t=0}^\infty \), sequences of joint distributions of wealth and talent \( \{h_t^n(b,z)\}_{t=1}^\infty \) for all \( n \), sequences of the bank branch distribution \( \{\Xi_t\}_{t=0}^\infty \), and prices \( \{r_t, w_t\}_{t=0}^\infty \) such that,

1. Agents of type \((b,z)\) living in market \( n \), optimally choose occupation \( o_t^n(b,z) \), credit entry \( g_t^n(b,z) \), consumption \( c_t^n(b,z) \), capital \( k_t^n(b,z) \), labor \( l_t^n(b,z) \), number of branch visits \( N_t^n(b,z) \), and average cash holdings \( m_t^n(b,z) \) by solving problem (4.11), given the credit entry costs \( \phi_t^n \) and transaction costs \( \zeta_t^n \) specified in equations (4.2) and (4.10).

2. The bank opens \( y_t \) branches in period \( t \) to maximize discounted profit (4.15).

3. The equilibrium interest rate \( r_t \) is determined by the capital market clearing condition in period \( t \):

\[
\sum_n P^n \int_{(b,z) \in E_t^n} k_t^n(b,z) h_t^n(b,z)_1 dbdz + \sum_n P^n \phi_t^n \int_{(b,z) \in Fin_t^n} h_t^n(b,z)_1 dbdz
= \sum_n P^n \int_{(b,z)} bh_t^n(b,z)_1 dbdz + \sum_n P^n \int_{(b,z)} s_t^n(b,z) h_t^n(b,z)_2 dbdz + \text{CAPITAL INFLOW}_t. \tag{4.17}
\]

where \( E_t^n \) is the set of working-period entrepreneurs in period \( t \) and market \( n \). \( Fin_t^n \) is the set of working-period entrepreneurs who pay the credit entry cost \( E_t^n \) in period \( t \) and market \( n \). The first term on the RHS of the equation is the amount of capital supplied by working-period agents. The second term on the RHS of the equation is the amount of capital supplied by leisure-period agents, with \( s_t(b,z) \) representing the average amount of deposit specified in (4.12).

4. The equilibrium wage \( w_t \) or the equilibrium population proportion of workers is determined by the labor market clearing condition in period \( t \):

\[
\sum_n P^n \int_{(b,z) \in E_t^n} l_t^n(b,z) h_t^n(b,z)_1 dbdz = \sum_n P^n \int_{(b,z) \in W_t^n} h_t^n(b,z)_1 dbdz \tag{4.18}
\]

where \( W_t^n \) is the set of working-period agents with types \((b,z)\), who choose to be workers in period \( t \) and market \( n \). Note that this condition determines the equilibrium population proportion of
workers $W^t_n$, if the equilibrium wage $w_t$ is the same as the subsistence return $f_t$; while it determines the equilibrium wage, if $w_t > f_t$.

(5). The distribution of wealth and talent $\{h^n_t(b,z), h^n_t(b,z)\}_{t=1}^\infty$ evolves according to the equilibrium mapping in all periods $t \geq 0$

$$h^n_{t+1}(\bar{b}, z)_1 = \int \mathbb{1}_{b' = \bar{b}} h^n_t(b, z) db, \quad \forall n.$$  

$$h^n_{t+1}(\bar{b}, z)_2 = \gamma \mu(z) \int \int \mathbb{1}_{b' = \bar{b}} h^n_t(b, z)_1 db dz + (1 - \gamma) \int \mathbb{1}_{b' = \bar{b}} h^n_t(b, z)_1 db, \quad \forall n. \quad (4.19)$$

where $b'$ represents the wealth at the beginning of the next period, and $\mathbb{1}_{b' = \bar{b}}$ is an indicator function which equals to one if $b' = \bar{b}$. Notice that the distributions of working-period and leisure-period alternate from $t$ to $t + 1$. Since agents only draw a new talent at the beginning of the working period, the term with $\gamma$ only enters the second equation.

5 Computation Strategy

We now propose an approximation algorithm to compute the equilibrium numerically. The model is hard to solve because in each period the bank needs to decide where to open branches. The branch opening decision requires the bank to solve a combinatorial programming problem, which is similar to the knapsack problem in decision science. Therefore, the bank’s problem is NP hard and solvable only when the number of markets is small.

In our model, there are $N = 1428$ markets among which $N_0 = 1020$ markets are candidates for new branch locations between 1986-1996. This makes the problem tremendously difficult, as the bank’s decision space becomes $\sum_{t=0}^T C_{y_t}^{y_t} C_{N_0 + y_t - \sum_{s=0}^{t-1} y_s}$ if $y_t$ branches are opened in period $t$ between 0 and $T$. Moreover, the bank’s problem interacts with the decisions of heterogeneous agents living in different markets, further increasing the computational complexity. Due to these reasons, we are only able to approximately solve the model by making several simplification assumptions.

5.1 Approximating the Bank’s Problem

We approximate the bank’s branch opening decisions using the decisions made by a myopic bank which only takes into account the current profit when opening branches. That is, instead of maximizing equation (4.15), the bank maximizes $\Pi_t$ when deciding where to open branches in period $t$. This approximation simplifies computation mainly because it allows us to inter-temporally disentangle the bank’s problem, reducing the decision space to $\sum_{t=0}^T C_{y_t}^{y_t} C_{N_0 + y_t - \sum_{s=0}^{t-1} y_s}$. However, even in this case, the problem is hard to solve as the bank still faces a huge number of combinations.\footnote{For example, in 1986, the bank opens 27 branches according to Table 1. Thus there are $C_1020^{27}$ possible combinations of new branch locations.}

To further simplify the problem, instead of searching for the entire space, we use an iteration method to approximate the optimal allocation. Specifically, in period $t$, we iterate the following search algorithm
In each iteration, we only allow the bank to open one branch, whose location is chosen to maximize total profit in period \( t \) based on a guess of the equilibrium interest rate and wage. Then, we check if the guess is consistent with the implied interest rate and wage that clear the market, after the branch is opened. If both the capital and labor markets are clearing, we update the credit entry costs and transaction costs in each market after including the new branch. Then, we move to the next iteration; otherwise, we form new guesses of the interest rate and wage until convergence is attained. This algorithm can be implemented in polynomial time, as the decision space is reduced to 

\[
\sum_{t=0}^{T} \sum_{s=0}^{y_t-1} C_{N_0+y_t-\sum_{s=0}^{y_t}(y_t-s)}^{y_t}.
\]

The approximation possibly generates bank locations different from the exact solution because it fails to consider three aspects of the dynamic programming problem. First, the endogenous evolution of wealth distribution over time would change the bank’s branch opening decision. That is, the heterogeneous savings rates would change the relative wealth distribution across markets and equilibrium prices over time, which would in turn change the profitability of branch opening in each market. Second, the branches opened by BAAC in future periods would change the bank’s branch opening decision. This is because BAAC branches attract customers and share profit, which would have differential effects across different markets on the profit that the bank would obtain. Third, the bank’s own future branch openings would also change the relative profitability across different markets, affecting the branch opening decision in the current period. After solving the approximating equilibrium, we assess how incorporating these “forward-looking” behavior would change the bank’s branch opening decisions (see Appendix D). We find that the first two aspects have very small effects on branch opening decisions, and the third one has a very limited effect. Thus, the approximation can roughly capture the branch locations that would be chosen by a forward-looking bank.

### 5.2 Approximating the Agent’s Problem

In spite of the simplification on the bank’s problem, the agent’s problem is still not tractable. The standard way to calculate the agent’s decision during transitions is to iteratively solve the value functions by backward induction, starting from the steady state. This requires the algorithm to guess and verify the equilibrium objects, including interest rates, wages and branch locations in each period along the transition path. Therefore, the agent’s problem is still NP-hard, even though the bank is myopic because the number of possible guesses of branch locations is \( \Pi_{t=0}^{T} C_{N_0+y_t-\sum_{s=0}^{y_t}(y_t-s)}^{y_t} \). To tackle the problem, we propose an approximation algorithm to solve the agent’s optimal decisions.

In our model, the agent has five decision variables: occupation, credit entry, the number of bank visits (i.e., cash holdings), consumption, and savings. The key decision variable is the amount of savings, which governs the inter-temporal wealth evolution. Conditional on a path of savings rates, occupation and credit entry decisions can be solved statically within the working period to maximize income, and the number of bank visits and consumption can be solved statically within the leisure period. The goal

\(^{25}\)If the model contains a single market as in Buera and Shin (2013), this algorithm is tractable because we only need to guess and verify equilibrium interest rates and wages. Since both interest rates and wages are continuous variables, efficient algorithms with polynomial complexity can be applied, for example, the bi-section method. The problem of guessing equilibrium branch locations is much more difficult because it is a combinatorial programming problem.
of our approximation algorithm is to closely proxy the savings rates that would be chosen by different agents in different markets.

In the following, we describe the main components of our algorithm. We provide a detailed step-by-step description of our algorithm in Appendix B and present the intermediate simulation results in Appendix E.

5.2.1 Algorithm

The logic behind our algorithm is to begin with a primitive model with myopic savings behavior and gradually modify the savings rates to reflect forward-looking savings behavior, in a way consistent with the equilibrium path of interest rates, wages, and bank locations. Our algorithm proceeds in three stages, which are described below.

Stage 1 We begin by specifying a Cobb-Douglas utility function for the agent as in Lloyd-Ellis and Bernhardt (2000). To elaborate, agents derive utility from consumption \( c_{t+1} \) and savings \( b_{t+2} \) in the leisure period by maximizing \( c_t^{1-\omega} b_t^\omega \), where \( c_{t+1} \) is the consumption in period \( t+1 \) and \( b_{t+2} \) is the amount of savings transferred to period \( t+2 \). Parameter \( \omega \) parsimoniously captures the savings motive and is set to be 0.25 following Jeong and Townsend (2008).

With the Cobb-Douglas utility function, the agent’s working-period and leisure-period problems can be solved separately:

\[
\begin{align*}
\max_{o_t, g_t} & \quad b_{t+1} \\
\text{subject to} & \quad b_{t+1} - b_t = (f_t + r_t b_t) \mathbb{I}_{o_t=0} + (w_t + r_t b_t) \mathbb{I}_{o_t=1} + (\mu_t^s \mathbb{I}_{g_t=0} + \mu_t^c \mathbb{I}_{g_t=1}) \mathbb{I}_{o_t=2}. 
\end{align*}
\]

(5.1)

\[
\begin{align*}
\max_{c_{t+1}, b_{t+2}, N_{t+1}} & \quad c_t^{1-\omega} b_t^\omega \\
\text{subject to} & \quad c_{t+1} + b_{t+2} \leq b_{t+1} + r_{t+1} (b_{t+1} - \frac{c_{t+1}}{2}) - \frac{r_{t+1} c_{t+1}}{2 N_{t+1}} - N_{t+1} \xi_{t+1}, \\
N_{t+1}, c_{t+1}, b_{t+2} & \geq 0.
\end{align*}
\]

(5.2)

The agent’s consumption in problem (5.2) has a closed-form solution:

\[
c_{t+1} = \frac{(1-\omega)[(1+r_{t+1})b_{t+1} - N_{t+1} \xi_{t+1}]}{1 + r_{t+1} (N_{t+1} + 1)/(2N_{t+1})}.
\]

(5.3)

Thus equation (5.3) can be solved jointly with equation (4.8) to obtain consumption \( c_{t+1} \) and the number of trips \( N_{t+1} \). These closed-form formulas make the agent’s problem highly tractable. We calibrate this primitive model to match a set of moments described in section 6 and simulate the model over 1986-1996. We then obtain the equilibrium bank locations, wealth distributions, interest rates, and wages along the whole transition path produced by the primitive model.

\[26\text{The value of } \omega \text{ will be modified in stage 2 and stage 3 to proxy the heterogeneous savings rates generated by forward-looking behavior. Therefore, setting a different initial value of } \omega \text{ does not affect our simulation results.}\]
Stage 2  Stage 1 essentially solves the equilibrium with myopic agents, who only consider current period utility when making savings decisions. The aggregate implication of the myopic savings behavior is very different because forward-looking agents have heterogeneous savings rates due to the self-financing motive (Buera, Kaboski and Shin, 2011; Moll, 2014). In stage 2, we introduce heterogeneous \( \omega \)s to proxy the heterogeneous savings rates.

Denote \( \bar{r} \) and \( \bar{w} \) as the average equilibrium interest rate and wage between 1986-1996 generated by the primitive model in stage 1. Consider an infinitely-lived agent entering working period \( t \) with wealth \( b_t = b \), talent \( z_t = z \), and CRRA utility \( u(c) = c^{1-\sigma} \). The agent lives in a market whose travel time to the nearest bank branch is \( d_t = d \) and faces the optimization problem (4.11) with \( r_t = \bar{r} \) and \( w_t = \bar{w} \) for all \( t \geq 0 \). We solve this problem for different values of \( (b,z,d) \) to obtain a function of savings rates in leisure period \( t+1 \):

\[
\tilde{s}_{t+1}(b,z,d) = 1 - \frac{c_{t+1}}{b_{t+1}},
\]

(5.4)

Since the agent is infinitely-lived, the savings rate does not depend on time \( t \). Thus we denote \( \tilde{s}(b,z,d) \) as the savings rate for the agent of type \( (b,z,d) \) in any period between 1986-1996. Using formulas (4.8) and (5.3), we derive the value of \( \omega(b,z,d) \) such that the myopic agent in stage 1 chooses the savings rate \( \tilde{s}(b,z,d) \):

\[
\omega(b,z,d) = 1 - \frac{(1 + \bar{r}/2)\sqrt{2b[1 - \tilde{s}(b,z,d)]} + \sqrt{\bar{r} \xi(d)}}{(1 + \bar{r})\sqrt{2b/[1 - \tilde{s}(b,z,d)]} - \sqrt{\bar{r} \xi(d)}},
\]

(5.5)

where \( \xi(d) \) is given by equation (4.10).

The introduction of state-dependent \( \omega(b,z,d) \) captures the heterogeneous savings rates chosen by forward-looking agents. Therefore, by imposing state-dependent \( \omega(b,z,d) \) in problem (5.2), we can proxy the savings rates chosen by forward-looking agents in a steady-state economy with interest rate \( \bar{r} \) and wage \( \bar{w} \). However, because the agents’ behavior is changed after imposing \( \omega(b,z,d) \), the new equilibrium prices at the new calibrated parameters will be different, which will in turn imply different state-dependent savings rates and \( \omega(b,z,d) \). Thus multiple iterations are conducted to get convergence in savings rates and \( \omega(b,z,d) \) as detailed in Appendix B.

Stage 3  Stage 2 essentially captures the savings decisions made by forward-looking agents in a steady-state economy with constant equilibrium interest rate and wage. However, it fails to capture the time-varying savings decisions along the whole transition path between 1986-1996. Specifically, the stage-2 algorithm cannot generate the effect of anticipating a future branch opening on the current savings rate. In stage 3, we introduce time-varying \( \omega \)s to deal with this issue.

The algorithm we develop is in the spirit of Buera, Kaboski and Shin (2011). We simulate the model with \( \omega(b,z,d) \) developed in stage 2 for a sufficiently longer time, keeping the bank distribution, capital inflows, and interest rate spread unchanged after 1996, to reach the economy’s steady state. Based on the equilibrium path of interest rates \( r_t \), wages \( w_t \), and bank locations \( \Xi_t \), we solve problem (4.11) for each agent of type \( (b,z) \) in each market \( n \) to obtain the savings rate \( s_{t+1}(b,z;n) \). Then using a formula similar to equation (5.5), we derive the time-varying market-specific omegas \( \omega_{t+1}(b,z;n) \) such that the myopic agent in stage 1 chooses the savings rate \( \tilde{s}_{t+1}(b,z;n) \).
As in stage 2, we have to do multiple iterations to get convergence in savings rates, omegas, interest rates, wages, and bank locations in each period. In principle, convergence is hard to obtain because it involves finding fixed points of a high-dimensional object. It is tractable to obtain convergence in our model because the model has two numerical properties.27 First, the bank’s branch opening decision is mostly determined by market size and the road network, but is not very sensitive to agents’ savings decisions. This implies that when we iterate the values of $\omega_{t+1}(b, z; n)$, bank locations will not be changed much. Second, the sensitivity of savings rates with respect to interest rates and wages is very similar between the stage-2 myopic agent that solves problem (5.2) and the forward-looking agent that solves problem (4.11).28 This implies that when adjusting the prices around the average equilibrium prices ($\bar{r}$ and $\bar{w}$), the implied $\omega$s would not change much.

6 Calibration and Validation Tests

In this section, we first discuss the calibration of model parameters. Then we conduct several out-of-sample validation tests to check whether the model can match several important characteristics at both the macro and micro level.

6.1 Calibration

We assume that the agent has CRRA utility with parameter $\sigma = 1.5$,

$$u(c) = \frac{c^{1-\sigma}}{1-\sigma}. \quad (6.1)$$

We set $\alpha = 0.33$ and $\nu = 0.16$ according to the estimate of Paweenawat and Townsend (2014) using Townsend Thai data.29 Their values are also close to the values used by Buera and Shin (2013) calibrated from the U.S. data. The one-year depreciation rate $\delta$ is set to be 0.08 according to the estimate of Samphantharak and Townsend (2009).

The other parameters are calibrated mainly from the data before 1986 (except for those variables that are not available), the year in which nation-wide financial reforms had not started yet. We calibrate the annual discount factor $\beta = 0.9$ to generate an initial interest rate $r_0 = 11.5\%$ consistent with the real interest rate in Thailand in 1986.

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27This is our conjecture after conducting several experiments. We are still in the process of implementing the algorithm.
28This is not true in the model of Lloyd-Ellis and Bernhardt (2000) because the savings rate is exactly equal to $\omega$ regardless of the interest rate and wage. Although our myopic agents have the same Cobb-Douglas utility function, the savings rates are varying with interest rates and wages due to cash holding motives. As shown in equation (5.3), the interest rate affects consumption through two effects. First, there is an income effect captured by the term $(1 + r_{t+1})b_{t+1}$ in the numerator, whereby agents become wealthier and consume more when the interest rate is higher. Second, there is a substitution effect captured by the term $r_{t+1}(N_{t+1} + 1)/(2N_{t+1})$ in the denominator, as when the interest rate is higher, agents prefer to substitute savings for consumption. At the calibrated parameters, the income effect dominates the substitution effect, so that when the interest rate is higher, agents save a smaller fraction of wealth. This is consistent with the interest rate sensitivity of savings rates chosen by forward-looking agents whose inter-temporal elasticity of substitution is below one.
29In Townsend Thai data, households’ production activities are classified as one of the four sectors: business, cultivation, fish and shrimp, or livestock. Cultivation activity is the most labor intensive, while fish and shrimp activity is the least labor intensive. Our calibration relies on the average estimates of the four activities weighted by the number of observations.
As documented by Jeong and Townsend (2007), more than 40% of the total labor force are working as subsisters during the period 1976-1986 and rapid wage rise only occurred in the 90s. Therefore, the wage rate in Thailand over this decade is mainly determined by the subsistence return in the agricultural sector. We thus calibrate the exogenous growth rate of the subsistence return to be $g_f = 0.5\%$ per year in order to match the annual average growth rate of wage income during the decade 1976-1986.

The parameters $\kappa$ and $\eta$ are calibrated to match the average nation-wide credit access ratio and the inequality of credit access conditions across markets in 1986. In particular, parameter $\eta$ enters equation (4.2) additively, and determines the overall credit entry cost. Its value mainly determines the nation-wide credit access ratio. Parameter $\kappa$ is multiplied by the travel time $d_t$ in equation (4.2), thus it controls primarily the variation in credit access conditions across markets. The value of this parameter is identified to match the Gini measure of credit access inequality.

We construct the nation-wide credit access ratio using SES. The 1986 survey documents whether any member of households has transactions with any formal financial institution in each month, such as commercial banks, savings banks, BAAC, government housing banks, financial companies or credit financiers. We consider a household as having access to credit if it has transactions with any formal financial institution in the previous month. Since SES does not provide a sufficiently large sample to capture the cross-sectional variation in credit access conditions, we use CDD to construct the credit access inequality, proxied by the Gini coefficient (see Figure 2 for the distribution of credit access conditions). In particular, the 1986 CDD census documents credit access conditions at the village level using a dummy variable, which is equal to 1 if the village headman reports to have loans from financial institutions. In our calculation, we assume that the whole village population has access to credit if the dummy variable is equal to 1. Otherwise, no one has access to credit. We then estimate the credit access ratio at the market level by aggregating the credit access information of villages that are nearest to each market.

Parameter $s$ in equation (4.10) captures the transaction fee which is estimated to minimize the discrepancy between the model generated average cash-to-wealth ratio and the actual cash-to-wealth ratio observed in the Townsend Thai survey data during the period 1998-2011 (see Figure 3). We construct total household net wealth as the sum of contributed capital, cumulative savings and insurance indemnity after adjusting for statistical discrepancy. We construct average cash holding using reported monthly flows of cash revenue and expenditure. We assume that households start with zero cash holding at the beginning of the survey year. Cash holding in each subsequent month is constructed using information on cash revenue and cash expenditure. For households with negative cash holding in certain months, we increase their initial cash holding such that the lowest cash holding in subsequent

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30The questionnaire asks the village headmen whether anyone in the village has access to credit from each one of several named institutions, including village funds, commercial bank, agricultural cooperatives, and trader or supplier of inputs (as a proxy for the informal).

31We use SES instead of CDD data to construct the nation-wide credit access ratio to follow the existing work (Gine and Townsend, 2004; Jeong and Townsend, 2008; Townsend and Ueda, 2010). SES provides a more reliable measure for the national credit access conditions because it is a representative household-level survey. In fact, CDD started to directly record the number of households in each village having access to credit since 1999. By plotting the nation-wide average credit access ratio between 1986-2011, we found a discrete jump in the year 1999, due to the change of measurement in CDD. The nation-wide average credit access ratio computed using CDD data after year 1999 is actually consistent with the SES, confirming that SES gives a more reliable measure.
months is zero.\footnote{Samphantharak and Townsend (2009) provide a detailed description on the construction of households’ balance sheet using Townsend Thai monthly surveys.}

The 1997 Townsend Thai annual survey has 10602 respondents reporting the number of years that household members have been doing the current work. This provides information to identify parameter $\gamma$, the probability of talent shocks. A higher value of $\gamma$ increases the chance of receiving talent shocks, thereby agents are more likely to change occupations. We calibrate the value of $\gamma$ to match the cumulative distribution of the number of years that households have stayed in their current occupations.

The tail parameter $\rho$ governs the distribution of talent, which affects relative business income and employment among entrepreneurs. This parameter is identified to match the employment share distribution. Following Dabla-Norris et al. (2015), we calculate the proportion of labor force employed by the 20% largest enterprises (sorted by total employment) from the 2006 World Bank Enterprise Survey of Thailand, and the value of $\rho$ is calibrated to match this moment.

The subsistence return in 1986, $f_0$, is identified to match the fraction of entrepreneurs in 1986. We construct the fraction of entrepreneurs using SES. There are four broad occupation categories documented in the 1986 survey: wage worker, farmer, nonfarm entrepreneur, and inactive. Following Gine and Townsend (2004), we consider a household as engaging in entrepreneurial activity if the head of the household is listed as a nonfarm entrepreneur. Since workers and subsisters co-exist in 1986 in both the data and model, the subsistence return $f_0$ is also the labor cost, which determines the profitability of business and entrepreneurship rate. In particular, identification is obtained since a higher value of $f_0$ increases the labor cost, resulting in a smaller fraction of entrepreneurs.

Households’ wealth is normalized by a scale parameter $q_w$ which transforms the wealth index to model units. We calibrate this parameter to equalize the average wealth in the data and the model generated steady-state value in 1986.

Finally, we are left with the collateral constraint parameter $\lambda$. In our model, parameter $\lambda$ captures the maximum possible loan-to-collateral ratio. We use the data on the amount of loan and collateral from the 1997 Townsend Thai annual survey to calibrate its value. After excluding households with negative amounts of collateral or loans, the sample consists of 893 households. However, in the data, some loans are under special contracts which require no collateral. This implies that the value of $\lambda$ is infinite in our model, which is obviously not informative about the true collateral friction. To deal with measurement errors and filter out such uncollateralized loan contracts, we set $\lambda = 20$ according to the 95th percentile of the loan-to-collateral ratio distribution. We validate that using the 85th or the 90th percentile as the cutoff does not change the quantitative results much. This micro estimate is also consistent with the structural estimate of Paulson and Townsend (2004).\footnote{Paulson and Townsend (2004) structurally estimate a model with limited liability, moral hazard, and a combination of both constraints using the data of Thailand. In their benchmark case, the estimated $\lambda$ is 20.8082 with standard error 1.4882.}

Note that the general equilibrium nature requires us to calibrate all eight parameters $\beta$, $\kappa$, $\eta$, $s$, $\gamma$, $\rho$, $f_0$, and $q_w$ jointly to match the relevant moments above. The calibration is conducted on the basis of the estimated wealth distribution, population, travel time, and initial bank distribution in 1986. In each round after a new set of parameters is selected, we first calculate agents’ optimal choices in different markets and find the equilibrium interest rate and wage that clear both the capital and labor markets.
Then we compute the relevant moments implied by the model and compare them with data (see Figure 9 and Table 2).

6.2 Validation Tests

We now conduct several validation tests to check whether the model can reproduce non-targeted moments and characteristics at both the macro and micro level. We first evaluate our model’s ability in predicting the bank’s branch opening decisions. Then we show that our model, calibrated mainly using data in 1986, is also able to capture the spatial variation in entrepreneurship and credit access ratios at the micro level in 1996. Finally, we show that our model can generate macro dynamics consistent with the data over the period 1986-1996, including GDP growth, income inequality, and credit access conditions.

6.2.1 Predictions on Bank Expansion

In Figure 10, we present the model-predicted branch locations and the actual branch locations in 1996. In general, our model is successful in capturing most of the branch locations. However, the model fails to predict the cluster of branches opened around the Bankok metropolitan area, and instead the model predicts more branch openings in the northern and eastern parts of the country. Our model fails to deliver more branch openings in the populous Bankok metropolitan area, mainly because bank branches have unlimited capacity of serving customers. If as in reality, the service time increases with the number of customers, then the bank should open more branches in populous areas. Moreover, the underlying environment across different markets is the same in our model, which does not capture the fact that Bankok has advantages in technology relative to other markets, attracting more bank branches. Panel C plots the percent of markets with correct prediction in a density map, overall the model is able to predict at least 60% of bank locations correctly for most areas.

Next, we zoom in on the provincial level and assess the dynamics of bank expansion. For each province, we compute the average discrepancy between the actual branch opening time and the predicted branch opening time. We set the timing difference to 10 years if either there is a branch opened in the data by 1996 but not predicted by the model, or vice versa. A smaller statistic indicates that the province has a better match between the model-predicted and the actual branch locations. In Figure 11 and 12, we report the province corresponding to the 2nd and 8th decile of this statistic. It is shown that even at the provincial level, our model predicts the dynamics of bank expansion quite well. This is remarkable since in each year, our calibration only sets the number of branch openings to match the national data but not for each province.

To further evaluate the model’s prediction, we compare the model-predicted branch locations with the prediction of a random assignment model. In the random assignment model, we ask the bank to randomly choose branch locations, which provides a benchmark with “no prediction” power.

We compute the fraction of locations with correct prediction in each year $t$. Figure 13 compares the prediction’s correction ratio of the two models. The dash line refers to the mean correction ratio of the random assignment model for 10000 times simulation. In 1996, about 65% of locations are predicted
correctly. The solid line represents the prediction of the baseline model, which outperforms the random assignment model in every year. In 1996, about 75% of the locations are predicted correctly.

Note that one important feature of our model is that it considers the economy’s network structure. When opening branches, the bank takes into account each branch’s impact on adjacent markets as shown in equation (4.16). For example, in Figure 14, without taking into the network effect, the bank would open a branch in the three most populous unbanked markets in 1990. However, our model predicts that the bank would instead open a branch in the upper-right market, which has a lower population (with 131033 households) compared to the market below it (with 169914 households). This is because the branch opened in a nearby market (with 172353 households) can already provide financial services at low costs, thus the profit generated from opening an extra branch in the third populous market is small.

6.2.2 Predictions on Spatial Variations and Aggregate Dynamics

Spatial Variations Figure 15 and Figure 16 evaluate the model’s ability in generating the observed spatial variation in entrepreneurship rates and credit access conditions across markets at the end of the policy intervention period. Panel As of Figure 15 and 16 present the fraction of households engaging in entrepreneurial activities and the credit access ratio in 1996. Panel Bs compare the model’s prediction with data. We use red color to represent the markets whose predicted entrepreneurship rates or credit access ratios are within 10 percentile rank order difference relative to the data. These can be considered as the markets predicted consistently with data. Clearly, our model captures most of the spatial variation in the Bangkok metropolitan area and south and north of this area along the central developed corridor of Thailand. The model over predicts entrepreneurship and credit access ratio in the eastern part of the country as our model incorrectly predicts more branch openings there (see Figure 10).

Overall, the model is able to capture the spatial variation in credit and entrepreneurship in about one third of the markets in Thailand. This is achieved due to three reasons: First, there is a statistically significant spatial correlation indicating that markets with branches or close to branches have higher entrepreneurship rates and credit access ratios. Second, our model is able to reproduce this correlation by specifying the geographical variation in credit entry costs. Third, the model-generated correlation is also roughly consistent with the data, spatially, because the bank branch locations in 1996 are also predicted reasonably well by the model.

Aggregate Dynamics We have shown that our model captures some of the spatial variation in credit access conditions and entrepreneurship. We also expect the model to perform well in generating the aggregate transitional dynamics if these micro variations are important features of the data. Figure 17 compares the model-predicted GDP growth, income inequality, and credit access conditions during the period 1986-1996 with those in the data.

In Thailand, the annual growth rate in real GDP per capita was below 4% in early 1980s. However, during the 1986-1996 period, the real GDP per capita was more than doubled, and the average annual growth rate at 8% even exceeded those neighboring East Asian miracle economies. Existing studies emphasize that factor accumulation, occupation transition, and financial deepening were jointly playing
a vital role in boosting economic output (see e.g., Gine and Townsend, 2004; Townsend and Ueda, 2006; Jeong and Townsend, 2008).

In Panel A, we observe that the movement of simulated GDP growth rate tracks the data. GDP growth accelerates sharply between 1986-1988, due to the sudden surge in capital inflows and bank expansion. The growth rate decreases between 1988-1993, when capital inflows recede, and increases again following a second wave of capital inflows. However, the model-predicted cumulative GDP growth during the decade is 67%, which only explains 57% of the 112% cumulative growth in the data. We attribute the difference partly to the growth in aggregate productivity, which was increased by 33% (measured as TFP based on growth accounting) during this decade but not captured by our model as the talent distribution is fixed over the decade.

Moreover, in terms of the timing of growth, our model generates higher growth rates in early years and lower growth rates in later years. Such a failure is caused by the diminishing returns in bank expansion. In our model, although the bank expands in every year, the impact of expansion on GDP growth is subject to diminishing returns. This is because in general the bank expands to wealthy and populous areas with priority, which constitute larger weights of the economy.

The rapid growth in GDP during this decade was accompanied with increased income inequality. As shown in panel B, the already high income Gini coefficient of Thailand at 0.489 in 1986, was increased to 0.535 in 1992, exceeding the average income Gini coefficient in Latin American and Caribbean countries at 0.502. After 1992, the Gini coefficient gradually decreased to 0.503 in 1996.

Our model is able to generate a Kuznets curve roughly in line with the data. However, the decrease in income inequality is predicted to be two years earlier than what happened in Thailand. In the model, the Gini coefficient starts to increase immediately in 1986, the year in which commercial banks initiated rapid expansion, and begins to fall in 1990. In the data, the Gini coefficient is stable between 1986-1988, increases from 1988 to 1992, and falls thereafter. Moreover, the simulated Gini coefficient is about 0.3 less compared with the data. The model fails to generate enough income inequality mainly due to the absence of two heterogeneity, the heterogeneity in workers’ income and the heterogeneity of underlying environment across different markets. Incorporating the fact that entrepreneurs around Bankok and the central development corridor have access to better technology and favorable market place will increase income inequality but we do not have rich enough data to estimate such heterogeneity.

As a result of financial liberalization policies, savings were mobilized and more households obtained access to credit. Panel C plots the trend of credit access ratio, which was almost stagnant before 1986 but more than doubled from 1986 to 1996, increasing from 10% to 26% in a decade. Financial liberalization not only increased the overall access to credit, but also improved credit access equality across different regions. As shown in Panel D, the Gini coefficient in credit access ratio computed using market-level data was reduced from 0.5 to 0.31 during this decade.

Both trends are well captured by our model. Note that matching the evolution of credit access conditions is not mechanical, although the number of branches opened by commercial banks is calibrated to match the data. This is because our calibration is conducted only to match the credit access conditions in 1986, not to minimize the discrepancy between model and data for the whole period 1986-1996. The quantitative impact of expanding branches on credit access ratio and inequality also depends on
households’ characteristics and where commercial banks expand, which are endogenous in our model. In our model, the improvement in credit access conditions comes from two sources. On the one hand, the expansion of branch network shortens the travel time and reduces the credit entry cost. On the other hand, the decreasing interest rate due to the inflows of international capital incentivizes entrepreneurs to obtain credit and expand their businesses. We analyze these effects in subsection 7.1.

7 Counterfactual Analyses

In this section, we conduct several counterfactual simulation experiments to understand the financial reform policies happened during 1986-1996 in Thailand.34 We first evaluate the contribution of bank expansion and capital account liberalization on GDP growth, income inequality, and credit access conditions. Then, we discuss the welfare and equilibrium implications of these reforms. Finally, we evaluate the role of credit provision and deposit mobilization caused by bank expansion.

7.1 Quantifying the Effect of Two Reforms

During the period 1986-1996, there are two major financial reforms as shown in Figure 1. One is the expansion of commercial banks and the other is the capital account liberalization which reduces the interest rate spread and results in an influx of international capital flows. In this subsection, we quantify the effect of each reform.

We study three counterfactuals: First, we evaluate what would happen if there were no reforms during this period. This experiment enables us to learn the position of Thailand on the previous transition path, and how far it is from the non-intervention steady state. Second, we consider the scenario where the expansion of commercial banks is the only reform initiated during this period by fixing the interest rate spread and capital flows at their initial values in 1986, 6.7% and -0.8% of GDP, respectively. Third, we consider what would happen if there were only capital account liberalization by shutting down completely the expansion of commercial banks and BAAC, i.e., the number of commercial bank and BAAC branches are fixed at 406 and 343 in our simulation, respectively.

7.1.1 Transitional Dynamics

Panel A of Figure 18 presents the simulated dynamics of GDP growth. When there is no reform, GDP growth rate is positive only in the late 80s and the cumulative growth is 6%. The counterfactual simulation indicates that half of the cumulative GDP growth in our baseline (33% out of 67%) is attributed to capital account liberalization. The sharp increase in net capital inflows from -0.8% of GDP in 1986 to 13.0% of GDP in 1990 increases annual GDP growth rate dramatically and reaches its peak of 11% in 1988. After 1990, GDP growth rate starts to decrease and becomes negative, due to receding capital inflows. In fact, the movement of GDP growth rate in the baseline tracks the movement of capital account liberalization counterfactual closely albeit with a milder fluctuation, indicating that capital inflows are the determining factor in generating two peaks in GDP growth rate.

34This section is based on the results of stage-1, we are currently in the process of implementing stage-2 and stage-3 algorithm.
Bank expansion alone increases GDP cumulatively by 25% during this decade, contributing to about one third of the baseline’s cumulative growth. The impact on GDP growth is diminishing over time as populated and wealthy markets are occupied with priority, which weigh more in accounting for the country’s GDP. Bank expansion promotes GDP growth through two channels, credit provision and deposit mobilization. On the one hand, bank expansion reduces the credit entry cost, especially for the markets located farther from the existing branches. This enables talented entrepreneurs living in these markets to obtain credit, and as a result, capital is more efficiently allocated among entrepreneurs. On the other hand, bank expansion reduces the transaction fee, allowing agents to hold less cash and more savings. This increases the supply of capital, resulting in more investment. We quantify the effect of each channel in the next subsection.

The financial policies during this decade in Thailand increase GDP through both capital deepening and capital reallocation. The deposit mobilization caused by bank expansion along with the influx of international capital flows increases the supply of capital, while the reduction in the interest rate spread lowers the cost of capital. All motivate entrepreneurs to invest more, increasing capital intensity. On the other hand, bank expansion leads to better and equalized credit provision, reallocating capital more efficiently to merited entrepreneurs through the market mechanism.

The equilibrium interest rates and wages are presented in Figure 19. Capital account liberalization increases the supply of capital, as a result, interest rate decreases. Bank expansion increases the supply of capital through the deposit mobilization channel, and increases the demand for capital through the credit provision channel by enabling talented entrepreneurs to obtain credit. At our calibrated parameters, the credit provision channel dominates, thus the interest rate increases after bank expansion. We return to this discussion in the next subsection. Moreover, panel A of Figure 19 reveals that the wage take-off is caused by capital account liberalization. Bank expansion does increase the demand for labor, however, the increase is not sufficient to move all subsisters to the wage/salary sector. As a result, the wage is growing at the exogenous growth rate of the subsistence return, $g_f$, in the counterfactual with only bank expansion.

Panel B of Figure 18 presents the simulated income inequality. Bank expansion reduces the Gini coefficient, since lower credit entry costs enable less wealthy agents to obtain credit and expand their businesses. By contrast, capital account liberalization exacerbates income inequality. This is because capital inflows increase the supply of capital, reducing the equilibrium interest rate. This, along with a decreasing trend in the interest rate spread, implies a lower cost of capital, which motivates the entrepreneurs with credit access to expand their businesses. Since these entrepreneurs on average have more income than the others, increasing their income further leads to higher inequality.

This suggests that the Kuznets curve in our baseline simulation results from the interaction between the two forces. Capital account liberalization contributes to the initial increase in the Gini coefficient before 1990. In later years, as capital inflows faded, the bank’s expansion kicks in with a dominating effect, generating a decrease in income inequality. Our finding complements the existing literature which argues that this Kuznets pattern of income inequality in Thailand coincides with the take off in wage and large movements of labor from the agricultural sector to the wage/salary sector (Gine and Townsend, 2004; Jeong and Townsend, 2008).
Panel C presents the evolution of the overall credit access ratio. Bank expansion and capital account liberalization contribute almost equally by 1996 to the increase in the credit access ratio. However, the credit access ratio in the capital account liberalization counterfactual fluctuates with the amount of capital inflows. The underlying mechanisms are also different. Bank expansion decreases the credit entry cost, which can be considered as relieving the ex-ante cost of credit provision. Capital account liberalization increases the credit access ratio by reducing the cost of capital, an ex-post cost of credit.

Panel D presents the dynamics of the market-level credit access Gini coefficient. Clearly, almost the entire decrease in credit access inequality is caused by bank expansion. Capital account liberalization almost has no impact on credit access inequality although it plays a significant role in determining the evolution of other macroeconomic aggregates. In fact, the decreasing credit access inequality generated by bank expansion partially translates into a decreasing income inequality, as agents from the markets with higher credit entry costs obtain credit and receive higher income.

7.1.2 Welfare Implications

We now study the welfare implication of these financial reforms. We measure individual welfare change based on the consumption increase from 1986 to 1996. The welfare change for each market is obtained by doing aggregation.

Figure 20 plots the average welfare change in the baseline simulation. There are significant difference in welfare change across different markets, ranging from 36% to 168%. Loosely speaking, the markets located farther away from the bank branches in 1986 are more likely associated with larger welfare gains. However, there are also markets located near these bank branches experience large welfare gains, and markets located away from these bank branches experience small welfare gains.

To understand what factors drive the spatial variation in welfare change, we investigate the welfare change under each financial reform policy using the counterfactual simulations described above.

Panel A of Figure 21 presents the welfare change due to bank expansion. It is shown that welfare increases in all markets, however, the magnitude varies across different markets. As bank expansion primarily benefits the regions that are previously excluded from financial intermediation, the markets located farther away from commercial bank branches in 1986 more likely to experience a larger welfare gain, about 56%-91%. The markets associated with the lowest welfare gain are either those already having bank branches in 1986 (around the Bankok metropolitan area), or those with no bank branches in 1996 (several markets in the northern and southern parts of the central corridor). This is because the financial access conditions in these markets are virtually unchanged, and the small 5% welfare gain is purely caused by the general equilibrium effect.

Panel B of Figure 21 presents the welfare change due to capital account liberalization. In contrast to Panel A, the markets with commercial bank branches in 1986 experience the largest welfare gain relative to other markets, by about 50%; while the markets that are distant from bank branches have about 29% welfare increases.

The two panels in Figure 21 uncover that the spatial variation in welfare change across different markets is jointly shaped by both capital account liberalization and bank expansion. Since the two financial reforms have opposite implications on the spatial distribution of welfare gains, this explains
why we observe the patterns in Figure 20.

### 7.1.3 Spatial correlation in workers’ and entrepreneurs’ welfare gains

The welfare gains caused by financial reforms incorporate both workers’ and entrepreneurs’ welfare change. To elucidate the exact channels and shed light on the within-market redistribution effect, we now zoom in on the welfare change of workers and entrepreneurs.\(^{35}\)

We measure the workers’ welfare change as the average consumption among workers in 1996 relative to the average consumption among workers in 1986. We measure the entrepreneurs’ welfare change similarly. Measuring the welfare change in this way enables us to obtain the improvement in the average standard living of either workers or entrepreneurs. However, note that the measured welfare change does not track the same group of agents between 1986 and 1996, since occupation choice is endogenous in our model. The workers in 1986 may become entrepreneurs in 1996 due to the change in market conditions or individual talent. Similarly, the entrepreneurs in 1986 may also become workers in 1996 due to these exogenous shocks.\(^{36}\)

#### Bank Expansion

In Panel A of Figure 22, we plot the change in workers’ welfare due to bank expansion. Notably, all workers experience a discernible welfare gain, which amounts to 21%-77% over the decade. Apart from the wage increase during the working period, the increase in the welfare of workers is due to two additional financial channels in the leisure period. First, workers living in markets that are distant from bank branches in 1986 may see their consumption increase due to lower transaction costs after bank expansion. Intuitively, consumption is negatively related to transaction costs because agents need to withdraw cash to purchase consumption goods (see equation 5.3). Second, there is a general equilibrium effect as bank expansion raises the interest rate, which encourages workers to consume more due to the income effect (see footnote 28). The former channel implies that workers living farther away from bank branches in 1986 are more likely to experience larger welfare gains due to the possible larger decrease in transaction costs.

Panel B of Figure 22 plots entrepreneurs’ welfare change. The spatial distribution in entrepreneurs’ welfare gains is similar to those of workers. That is, entrepreneurs living farther away from bank branches in 1986 are more likely to experience larger welfare gains. However, the magnitude of the spatial variation for entrepreneurs’ welfare gains is much larger, ranging from 75% to 273%. This is due to an additional financial channel for entrepreneurs in the working period. Bank expansion reduces the credit entry costs which allows more entrepreneurs to have credit access and make more profit.

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\(^{35}\)We do not discuss farmers’ welfare change since they are associated with the same level of income as workers, if they are existing in the economy.

\(^{36}\)An alternative way to measure workers’ welfare change is to focus on workers in 1986 to avoid the selection effect. However, we find that this measurement is not informative about the change in the standard living of workers, since most of the increase in welfare is due to the change in occupation caused by talent shocks. This is because most workers in 1986 are associated with low talent, and mechanically a large fraction of them will be lucky to draw high talent shocks during the decade and become entrepreneurs. Given that entrepreneurs have much higher consumption compared to workers, we would measure a significant increase in workers’ welfare attributed to talent shocks, instead of financial reforms. On the other hand, most entrepreneurs in 1986 are associated with high talent, and mechanically a large fraction of them will be unlucky to draw low talent shocks during the decade and become workers. As a result, we would measure a significant decrease in entrepreneurs’ welfare regardless of financial reforms.
significantly increases the wealth and consumption for entrepreneurs living farther away from bank branches in 1986, as they were previously excluded from the credit market due to the high entry costs.

**Capital Account Liberalization** In Figure 23, we present the change in workers’ and entrepreneurs’ welfare due to capital account liberalization. All workers experience a moderate increase in welfare, by about 4%-7%, due to the higher wage in 1996. By contrast, entrepreneurs experience very large welfare gains, by about 270%-370%, suggesting that capital inflows mainly benefit entrepreneurs.

The spatial distribution in welfare gains is also different for workers and entrepreneurs. As shown in Panel A of Figure 23, workers away from bank branches in 1986 experience larger welfare gains. This is because workers who live farther away from bank branches consume less due to high transaction costs (see equation 5.3). As a result, the uniform increase in the country-wide equilibrium wage would boost their consumption by a larger proportion.

For entrepreneurs, capital account liberalization has an opposite implication on the spatial distribution in welfare gains (see Panel B of Figure 23). The lower deposit rate and interest rate spread incentivize entrepreneurs to invest more capital. However, the ability to expand production scale depends on the location where entrepreneurs operate their businesses. In particular, entrepreneurs living in the markets that are distant from bank branches face high credit entry costs, thus they choose to self finance. As a result, they do not receive the benefits from capital account liberalization. This suggests that entrepreneurs living in the markets closer to bank branches would benefit more from capital account liberalization because of better credit access.

It seems counter intuitive that even entrepreneurs living farther away from bank branches still experience a large welfare increase by about 270% on average. Presumably these entrepreneurs should not benefit from capital account liberalization since they do not borrow from the credit market. In fact, the welfare increase is purely caused by a positive selection effect. The capital inflows increase the supply of capital but not the supply of labor. Therefore, as entrepreneurs living closer to bank branches obtain credit and expand their businesses, the equilibrium wage increases (see Figure 19). The higher equilibrium wage crowds out less talented entrepreneurs out of their businesses, which generates a positive selection effect on average welfare.37

**Discussion** The analyses above suggest that bank expansion and capital account liberalization have opposite implications on the spatial correlation between workers and entrepreneurs’ welfare gains. As shown in Figure 24, bank expansion generates a positive spatial correlation between workers’ and entrepreneurs’ welfare change; while capital account liberalization generates a negative one.

7.1.4 **Equilibrium Effects**

In this subsection, we discuss and quantify the effect of policy reforms in partial equilibrium and in general equilibrium. The purpose is to see how the movement in interest rates and wages would affect

37Note that the lower interest rate generates a negative selection effect that encourages less talented agents to start businesses. However, this effect is very small in the markets farther away from bank branches, as entrepreneurs living in these markets choose to self finance. Therefore, in the markets away from bank branches, there is only a positive selection effect on the average welfare of entrepreneurs.
Table 3 compares the partial-equilibrium and general-equilibrium outcomes of all policy experiments discussed before. In the baseline simulation, the welfare gain increases from 65.9% to 87.3% when prices are fixed and GDP increases sharply from 67.2% to 92.0%. Income inequality and credit access ratio also increase more in partial equilibrium as the change in Gini coefficient moves from 0.005 to 0.032. These observations are consistent with the movement of prices in Figure 19. The policy reforms initiated during this period raise both wages and interest rates in 1996, which arguably benefit workers. When these general equilibrium effects are excluded, entrepreneurs would face much lower production costs, allowing them to expand their businesses and make more profit.

In the counterfactual of capital account liberalization, we find that the effect on all variables of interest is smaller in partial equilibrium. This is because capital account liberalization includes two policy reforms, capital inflows and decreasing interest rate spread, both affecting the economy by reducing the cost of capital. The capital inflows increase the supply of capital, thus affecting the economy purely through the general equilibrium effect of lowering the interest rate. Therefore, capital inflows would have no effect on the real economy if the interest rate and wage are fixed. The increase in welfare and GDP in partial equilibrium reflects the effect of decreasing interest rate spread.

The counterfactual of bank expansion has a larger increase in welfare and GDP in partial equilibrium. This is because bank expansion induces a higher interest rate as shown in Figure 19. Moreover, wage also increases at the subsistence return between 1986-1996 due to the coexistence of farmers and workers. In partial equilibrium, the two prices are fixed at lower values in 1986, which allows entrepreneurs to face lower production costs and expand businesses. This in turn, increases the income Gini coefficient and the credit access ratio.

7.2 Quantifying the Role of Credit Provision and Deposit Mobilization

The bank’s expansion of branch network reduces both the credit entry cost and the transaction fee. The former allows more entrepreneurs to obtain credit and improves the efficiency of capital allocation. The latter mobilizes savings and channels financial resources to the production sector. Figure 25 and 26 compare the simulated spatial distribution of bank credit and deposit in 1986 and 1996. It is clear that after bank expansion, credit almost penetrates to the entire country. The deepening of deposit mobilization is not as significant as credit provision. This is because at our calibrated parameters, the fraction of cash holdings is less sensitive to the travel time to nearest branch according to the data (Figure 3). However, we can still see in Figure 26 that the level of deposit increases in almost every market.

Both credit provision and deposit mobilization have impact on GDP growth and welfare. To separate one from the other, we simulate two counterfactuals with either the credit entry cost or the transaction fee being fixed at its initial value. In one counterfactual, we fix the transaction fee in each market at its value in 1986 (i.e., the travel time \( d_i \) in formula (4.10) is fixed). This implies that the expansion of bank branches would only reduce the credit entry cost but not the transaction fee. This isolates the channel of credit provision. In the other counterfactual, we fix the credit entry cost in each market at its value in 1986 (i.e., the travel time \( d_i \) in formula (4.2) is fixed). As a result, bank expansion only reduces the transaction fee but not the credit entry cost. This isolates the channel of deposit mobilization.
7.2.1 Transitional Dynamics

We compare the simulated transitional dynamics of each counterfactual with the transitional dynamics of bank expansion. Figure 27 presents the simulation results.

Panel A shows that the channels of credit provision and deposit mobilization have roughly equal contribution to GDP growth during the period 1986-1996. Credit provision generates 17% cumulative GDP growth and deposit mobilization generates 12% during this decade. Notably, we see that the impact of credit provision is small initially in 1986 and reaches its peak with a one year lag. This suggests that the initial nationwide credit entry cost in 1986 is very high, and it takes a while for bank expansion to improve credit provision.

Panel B shows that credit provision and deposit mobilization have opposite impacts on income inequality. If bank expansion only reduces the transaction fee, income inequality would first rise and then decrease. This is because deposit mobilization affects income inequality through two channels: First, as what capital account liberalization does, it increases the supply of capital and lowers the equilibrium interest rate. Facing a lower cost of capital, entrepreneurs would expand their businesses and make more profit, which exacerbates income inequality. However, different from capital account liberalization, deposit mobilization also increases savings, allowing both entrepreneurs and workers to have more interest earnings. Since interest earnings account for a larger fraction of worker’s income, this savings channel reduces income inequality. By contrast, credit provision reduces the income Gini coefficient, as it enables relatively poorer agents to obtain credit and earn higher income.\(^{38}\) Moreover, the movement of income Gini caused by the credit provision channel alone tracks the Gini curve of the fully functioning bank closely (solid line). This indicates that the decreasing part of the Kuznets curve in Figure 17 is mostly driven by the reduction in the credit entry cost.

Panel C shows that the credit provision channel contributes to about two third of the increase in the credit access ratio. However, deposit mobilization has almost no effect on financial inclusion. Panel D offers a consistent finding—almost the entire reduction in credit access inequality is explained by the credit provision channel. This is intuitive since lower the credit entry cost directly incentivizes entrepreneurs to borrow, but deposit mobilization only works indirectly through the change in equilibrium interest rates. Note that although deposit mobilization has a very limited impact on financial inclusion when acting on its own, it amplifies the impact of the credit provision channel. As shown in Panel C, allowing the bank to mobilize savings shifts the dashed line to the solid line, raising the credit access ratio by about 2%. This suggests that the two channels are complementary in boosting the credit access ratio. In fact, reducing the credit entry cost generates an upward pressure on the equilibrium interest rate as entrepreneurs increase their demand for capital. This upward pressure potentially increases the cost of capital and pushes entrepreneurs to stay away from credit, limiting the effect of credit provision on financial inclusion. Deposit mobilization brings an amplification effect precisely because it increases the supply of capital and lowers the equilibrium interest rate, which is especially valued when the credit entry cost is low.

\(^{38}\) The credit provision channel captures the reduction in the credit entry cost following bank expansion. Therefore, our model provides a micro foundation for the policy evaluation “reducing the participation cost” considered by Dabla-Norris et al. (2015). The reduction in income inequality is also consistent with their comparative statics.
Figure 28 plots the equilibrium interest rates and wages. As mentioned before, bank expansion does not generate sufficient forces to move subsisters to the wage/salary sector. As a result, the wage is stagnant. Deposit mobilization promotes GDP through the capital deepening channel, by increasing the supply of capital and by lowering the interest rate. Credit provision increases GDP through the capital reallocation channel, by enabling talented entrepreneurs to upgrade the size of their businesses. At the calibrated parameters, the credit provision channel dominates the deposit mobilization channel, resulting in a higher interest rate after bank expansion. We obtain this result because the parameter $\kappa$ in the credit entry cost (equation 4.2) is calibrated to be a large value in order to match the high credit access inequality in 1986. A larger $\kappa$ increases the sensitivity of the credit entry cost with respect to the travel time to the nearest bank branch, as a result, bank expansion would have a larger impact on reducing this cost, making the credit provision channel stronger.

7.2.2 Sensitivity Analysis

In Table 4, we conduct a sensitivity analysis to illustrate how the parameters governing the variation in credit entry costs and transaction costs affect the relative importance of the credit provision and the deposit mobilization channels. We consider what would happen after bank expansion if the initial friction due to credit entry costs is larger by increasing $\kappa$ from its calibrated value 0.45 to 0.8. Column 2 shows that, as bank expansion mitigates this friction through the credit provision channel, the contribution of the credit provision channel also increases from 68% in the benchmark case to 80% while the contribution of the deposit mobilization channel decreases from 48% to 32%. Moreover, when the initial friction in credit entry costs across different markets is large, bank expansion also increases the demand for capital more through the credit provision channel comparing to the benchmark case (44% v.s. 42%). In column 3, we consider what would happen after bank expansion if the initial friction due to transaction costs (i.e., inequality in cash-to-wealth ratio across markets) is larger by increasing $s$ from its calibrated value 0.0051 to 0.01. In this case, the contribution of deposit mobilization increases from 48% to 59% while the credit provision channel becomes less important compared to the benchmark case. Moreover, due to the larger friction in transaction costs in 1986, capital supply (i.e., the total amount of deposit) increases by 10% in 1996, which is 3% larger than what happens in the benchmark case.

Therefore, in principle, the relative significance of credit provision and deposit mobilization depends crucially on parameters governing the initial financial frictions in 1986. That is, the large credit access inequality in 1986 and the small spatial variation in cash holdings jointly imply that the credit channel is relatively stronger compared to the deposit mobilization channel.

8 Conclusion

In this paper, we develop a novel dynamic equilibrium model with local spatial markets in which heterogeneous agents face differential financial frictions. We apply the model to understand, evaluate, and quantify the impact of financial reforms on GDP growth, financial inclusion, inequality, and welfare in Thailand. The model is calibrated using detailed household and GIS data before government intervention, and can match a set of micro and macro aspects of the Thai economy.
We find that both bank expansion and capital account liberalization contribute significantly to GDP growth but have different implications on income inequality and welfare. This is because capital account liberalization impacts the economy through the capital deepening channel while bank expansion not only deepens the capital base but also reallocates capital to more talented entrepreneurs. There is an interesting spatial correlation between workers’ and entrepreneurs’ consumption gains. As a consequence of bank expansion, both workers and entrepreneurs are associated with larger increase in consumption if they live farther away from bank branches in 1986. However, in these markets, capital account liberalization results in larger consumption gains for workers but lower consumption gains for entrepreneurs.
References


Note: Panel A plots the trend of interest rate spread (prime lending rate minus deposit rate) between 1986-1995. Data are from various issues of *Financial Institutions and Markets in Thailand*, published by Bank of Thailand. Panel B plots capital flows between 1980-1996. Data are from Alba, Hernandez and Klingebiel (1999, Figure 2) and the Bank of Thailand. The Bank of Thailand includes nonbank and bank capital flows. The former includes foreign direct investment, portfolio capital, nonresident baht accounts, trade credits, and syndicated borrowing by domestic corporates from oversea financial institutions. The bank flows are resident banks borrowing from overseas sources. Panel C plots the number of commercial bank and BAAC branches opened in different locations. The branch location data are constructed using GIS (see section 2 for details).

Figure 1: The trend of interest rate spread, capital flows, and the number of commercial bank and BAAC branches during 1981-1996.
Note: We use CDD to construct the credit access ratio in each village and map them to markets defined in subsection 4.1.1. The CDD census documents credit access conditions at the village level using a dummy variable, which is equal to 1 if the village headman reports to have loans from financial institutions. In our calculation, we assume that the whole village population has access to credit if the dummy variable is equal to 1. Otherwise, no one has access to credit. We then estimate the credit access ratio at the market level by aggregating the credit access information of villages within each market. When calculating the spatial correlation, we use the threshold of 300 km to determine spatial neighbors, which maximizes the z-score (an indicator of the intensification of clustering). The country-wide p-value is < 0.0001 computed from Moran’s test.

Figure 2: Distribution of credit access ratios and commercial bank branches.
Note: Data are from the Townsend Thai monthly panel surveys, which were conducted in 16 villages for 40 households in each village during 1998-2011. We construct total household net wealth as the sum of contributed capital, cumulative savings and insurance indemnity after adjusting for statistical discrepancy. We construct average cash holdings using reported monthly flows of cash revenue and expenditure. We assume that households start with zero cash holding at the beginning of the survey year. Cash holding in each subsequent month is constructed using information on cash revenue and cash expenditure. For households with negative cash holding in certain months, we increase their initial cash holding such that the lowest cash holding in subsequent months is zero. Panel A plots the average households’ cash to wealth ratio among all 16 villages between 1998-2002 against the deposit interest rate, obtained from World Development Indicators (WDI). Panel B plots the average cash to wealth ratio in each village against the car travel time to the nearest bank branch. The percent of wealth held in cash at the village level is calculated as the average households’ cash to wealth ratio over this period.

Figure 3: The average cash to wealth ratio for households living in 16 villages during 1998-2011.
Note: Panel A plots the bank locations, market boundaries, road networks, and population for province Buriram in Thailand using the GIS data. The blue dots represent commercial bank locations and the grey dots represent villages in 2011. The blue lines plot the border of each market. The grey lines represent the road networks. For clarity, we only plotted road types 1-5 (see Table E.1), although when calculating the travel time we consider all road types 1-7. The color of each market represents the market size. Panel B plots the model economy abstracting from Panel A. The blue nodes represent bank locations, and the distance between each pair of nodes is measured using the car travel time from the GIS data.

Figure 4: An illustration of markets and the model’s network structure.
Note: This figure presents the estimated market-level population density. We estimate the population of each market using the data on village population from CDD and the data on municipal population from PHC in 1990. The population density is computed as the population of each market divided by the market's area.

Figure 5: Estimated market-level population density.
Note: This figure presents the histogram of all 19519 villages’ wealth index in Thailand. The solid curve is the estimated national wealth distribution by fitting the histogram using a double exponential function. The dashed curve illustrates the shape of the wealth distribution in a particular market whose mean wealth index is 70% of the mean wealth index in Thailand.

Figure 6: Estimation of the wealth distribution.
Note: This figure presents the cross-market variation from the estimation of the market-level wealth index, constructed from the mean village-level wealth index of the nearest villages assigned to each market. Our estimation is based on the wealth index of 19519 villages, which is constructed using the first principal component vector of three durable assets, including per capita TV ownership per village, per capita motorcycles per village, and per capita pickup vehicles per village (Assuncao, Mityakovy and Townsend, 2012).

Figure 7: Estimated initial household cross-market wealth dispersion in 1986.

Figure 8: Timing of agents’ problem.
Note: Panel A plots the cash-to-wealth ratio against the car travel time to the nearest bank branch. Panel B plots the fraction of people that has been staying in current occupations for at least $t$ years. In both panels, circles represent the data.

Figure 9: Calibrating parameters $s$ and $\gamma$: cash-to-wealth ratio and the persistence of occupation in the model and data.
Note: In panel A, we plot the locations where the model’s prediction is correct. The solid dots represent the locations with branches in the data, which are also predicted by the model. The hollow dots represent the locations without branches in the data and not predicted by our model. In panel B, we plot the locations where the model’s prediction is inconsistent with the data. The hollow dots represent the locations with branches in the data, but not predicted by our model. The solid dots represent the locations where the bank in our model opens branches but not in the data. In panel C, we plot the percent of markets with correct prediction based on the markets within 30km of each bank location.

Figure 10: The distribution of commercial bank branches in 1996: model v.s. data.
Note: This figure compares the model-predicted and actual bank locations from 1986 to 1996 in province Surin. Each market is represented by a hollow circle (0, 0). The circle is filled with red color if there is a branch predicted by the model (0, 1). The circle is plotted with a thick dark blue edge if there is a branch in the data (1, 0). Thus, the circle with a dark blue edge and filled with red color indicates that the model has a prediction consistent with the data (1, 1). The average timing discrepancy between model-predicted and actual bank location is 2.9 years in this province.

Figure 11: Model-predicted and actual bank locations in the province (Surin) corresponding to the 2nd decile of the branch opening timing discrepancy.
Note: This figure compares the model-predicted and actual bank locations from 1986 to 1996 in province Ubon-Ratchathani. Each market is represented by a hollow circle (0,0). The circle is filled with red color if there is a branch predicted by the model (0,1). The circle is plotted with a thick dark blue edge if there is a branch in the data (1,0). Thus, the circle with a dark blue edge and filled with red color indicates that the model has a prediction consistent with the data (1,1). The average timing discrepancy between model-predicted and actual bank location is 5.5 years in this province.

Figure 12: Model-predicted and actual bank locations in the province (Ubon-Ratchathani) corresponding to the eight decile of the branch opening timing discrepancy.
Figure 13: Comparing the prediction correctness on branch locations to a random assignment model. The 99% bound is plotted based on 10000 simulations of the random assignment model.
Note: This figure illustrates the difference in branch opening strategies adopted by the bank in our model and the bank without noticing the network effect. Each market is represented by a hollow circle (0, 0). The circle is filled with red color if there is a branch predicted by the model (0, 1). The circle is plotted with a thick dark blue edge if there is a branch in the data (1, 0). Thus, the circle with a dark blue edge and filled with red color indicates that the model has a consistent prediction with the data (1, 1). The numbers around each market represent market population (market size).

Figure 14: An illustration of the network effect on branch openings.
Note: Panel A plots the percent of entrepreneurs at the market level in 1996. We use CDD to construct the percent of entrepreneurs in each village and map them to markets. The CDD census does not document the number of households engaged in entrepreneurial activities in each village. Following Felkner and Townsend (2011), we consider households working in retail and cottage industries as engaged in entrepreneurial activities. Paulson and Townsend (2004) use household-level Townsend Thai data and report that the most common enterprise is a shrimp pond, followed by trader, and then shop, which supports this classification. Panel B presents the difference in entrepreneurship between model and data. Instead of computing the relative difference, we construct the difference in entrepreneurship as the discrepancy in percentile rank of the fraction of entrepreneurs between model and data for each market. Light blue represents the markets where the model under predicts the reality by more than 10 percentile rank order and dark blue represents over prediction by 10 percentile rank order. Red color highlights predictions with percentile rank difference within 10 percentile. We employ the percentile rank difference to deal with the noise in measurement due to the different datasets used in calibration and evaluation. When calibrating model parameters we use the SES dataset, which is a nationally representative household survey. However, the SES dataset does not cover all regions. Thus the data used in constructing the spatial variation are from the CDD survey. The CDD survey is suffered more from measurement errors, as it does not directly document entrepreneurship. For example, in the SES data, 15% of households engage in entrepreneurial activities in 1996, while in CDD, 4.5% of households are entrepreneurs according to our classification.

Figure 15: Prediction on market-level entrepreneurship in 1996.
Note: Panel A plots the percent of households with access to credit at the market level in 1996. We use CDD to construct the credit access ratio in each village and map them to markets. The CDD census documents credit access conditions at the village level using a dummy variable, which is equal to 1 if the village headman reports to have loans from financial institutions. In our calculation, we assume that the whole village population has access to credit if the dummy variable is equal to 1. Otherwise, no one has access to credit. We then estimate the credit access ratio at the market level by aggregating the credit access information of villages that are within each market. Panel B presents the difference in credit access ratio between model and data. Instead of computing the relative difference, we construct the difference in credit access ratio as the discrepancy in percentile rank of the credit access ratio between model and data for each market. Light blue represents the markets where the model under predicts the reality by more than 10 percentile rank order and dark blue represents over prediction by 10 percentile rank order. Red color highlights predictions with percentile rank difference within 10 percentile. We employ the percentile rank difference to deal with the noise in measurement due to the different datasets used in calibration and evaluation. When calibrating model parameters we use the SES dataset, which is a nationally representative household survey. However, the SES dataset does not cover all regions. Thus the data used in constructing the spatial variation are from the CDD survey. The CDD survey is suffered more from measurement errors, as it does not directly document credit access conditions for each household. For example, in the SES data, 26% of entrepreneurs have access to credit in 1996, while in CDD, 40% of households have credit access.

Figure 16: Prediction on market-level credit access conditions in 1996.
Figure 17: GDP, income inequality, credit access ratio and inequality during the period 1986-1996.
Note: The solid line represents the baseline simulation, where all reforms were in effect. The dashed line represents the counterfactual with only bank expansion. The dash-dotted line represents the counterfactual with only capital account liberalization. The dotted line represents the counterfactual with no reforms.

Figure 18: Counterfactual analysis.

Note: The solid line represents the baseline simulation, where all reforms were in effect. The dashed line represents the counterfactual with only bank expansion. The dash-dotted line represents the counterfactual with only capital account liberalization. The dotted line represents the counterfactual with no reforms.

Figure 19: The dynamics of wages and deposit rates in counterfactual policy analysis.
Note: The yellow dots represent the commercial bank locations in 1986. Darker colors refer to larger increase in welfare.

Figure 20: Welfare change in baseline simulation.
Note: The yellow dots represent the commercial bank locations in 1986. Panel A and B present the welfare change due to bank expansion and capital account liberalization, respectively. In both panels, darker colors refer to larger increase in welfare.

Figure 21: Simulated counterfactual welfare change due to bank expansion and capital account liberalization.
Note: The yellow dots represent the commercial bank locations in 1986. Panel A and B present the welfare change for workers and entrepreneurs due to bank expansion. In both panels, darker colors refer to larger increase in welfare.

Figure 22: Simulated counterfactual welfare change for workers and entrepreneurs due to bank expansion.
Figure 23: Simulated counterfactual welfare change for workers and entrepreneurs due to capital account liberalization.

Figure 24: Simulated counterfactual welfare change for workers and entrepreneurs due to capital account liberalization and bank expansion (scatter plot).
Note: The yellow dots represent the predicted bank locations. Panel A and B present the amount of bank credit at the market level in 1986 and 1996, respectively. In both panels, darker colors refer to higher levels of credit.

Figure 25: Simulated bank credit in 1986 and 1996.
Figure 26: Simulated bank deposit in 1986 and 1996.

Note: The yellow dots represent the predicted bank locations. Panel A and B present the amount of bank deposit at the market level in 1986 and 1996, respectively. In both panels, darker colors refer to higher levels of deposit.
Figure 27: Quantifying the effects of credit provision and deposit mobilization.

Figure 28: The dynamics of wages and deposit rates in deposit mobilization and credit provision.
Table 1: Calibration of policy reform parameters

<table>
<thead>
<tr>
<th>Parameters</th>
<th>86</th>
<th>87</th>
<th>88</th>
<th>89</th>
<th>90</th>
<th>91</th>
<th>92</th>
<th>93</th>
<th>94</th>
<th>95</th>
</tr>
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<tbody>
<tr>
<td>( y_t )</td>
<td>27</td>
<td>41</td>
<td>17</td>
<td>19</td>
<td>77</td>
<td>80</td>
<td>42</td>
<td>33</td>
<td>46</td>
<td>49</td>
</tr>
<tr>
<td>( \chi_t )</td>
<td>7.7</td>
<td>7.5</td>
<td>6.6</td>
<td>5.0</td>
<td>3.4</td>
<td>3.9</td>
<td>6.7</td>
<td>4.3</td>
<td>3.3</td>
<td>2.5</td>
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<tr>
<td>CAPITAL INFLOW(_t) (% of GDP)</td>
<td>-0.8</td>
<td>2.2</td>
<td>6.1</td>
<td>8.2</td>
<td>13.0</td>
<td>10.7</td>
<td>8.4</td>
<td>8.6</td>
<td>13.1</td>
<td>9.5</td>
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</table>

Note: The data on net capital flows in each year come from the Bank of Thailand as reported in Alba, Hernandez and Klingebiel (1999). The data on interest rate spreads are from various issues of Financial Institutions and Markets in Thailand, published by Bank of Thailand. The branch location data are constructed using GIS (see section 2 for details).

Table 2: Calibration of model parameters

<table>
<thead>
<tr>
<th>Target moments</th>
<th>Data</th>
<th>Model</th>
<th>Parameters</th>
</tr>
</thead>
<tbody>
<tr>
<td>Occupation persistence</td>
<td>Figure 9, panel B</td>
<td>( \gamma = 0.352 )</td>
<td></td>
</tr>
<tr>
<td>Average cash-to-wealth ratio</td>
<td>Figure 9, panel A</td>
<td>( s = 0.0051 )</td>
<td></td>
</tr>
<tr>
<td>Average credit access ratio</td>
<td>0.105</td>
<td>0.102</td>
<td>( \eta = 1.1 )</td>
</tr>
<tr>
<td>Credit access inequality</td>
<td>0.500</td>
<td>0.502</td>
<td>( \kappa = 0.45 )</td>
</tr>
<tr>
<td>Fraction of entrepreneurs</td>
<td>0.15</td>
<td>0.14</td>
<td>( f_0 = 0.48 )</td>
</tr>
<tr>
<td>Top 20% employment</td>
<td>0.722</td>
<td>0.720</td>
<td>( \rho = 4.7 )</td>
</tr>
<tr>
<td>Average wealth</td>
<td>0.266</td>
<td>0.266</td>
<td>( q_w = 0.209 )</td>
</tr>
<tr>
<td>Wage growth rate, 76-86</td>
<td>0.5%</td>
<td>0.5%</td>
<td>( g_f = 0.5% )</td>
</tr>
<tr>
<td>Interest rate in 86</td>
<td>11.5%</td>
<td>11.5%</td>
<td>( \beta = 0.9 )</td>
</tr>
<tr>
<td>Loan-to-collateral ratio, 95% quantile</td>
<td>20</td>
<td>20</td>
<td>( \lambda = 20 )</td>
</tr>
<tr>
<td>Estimates from Paweenawat and Townsend (2014)</td>
<td>( \nu = 0.16 )</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Estimates from Paweenawat and Townsend (2014)</td>
<td>( \alpha = 0.33 )</td>
<td></td>
<td></td>
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<tr>
<td>Estimates from Samphantharak and Townsend (2009)</td>
<td>( \delta = 0.08 )</td>
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Table 3: Evaluation of financial reforms in partial equilibrium and general equilibrium.

<table>
<thead>
<tr>
<th></th>
<th>Welfare (%)</th>
<th>GDP (%)</th>
<th>Income Gini</th>
<th>Credit Access Ratio (%)</th>
<th>Gini</th>
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<tr>
<td>Baseline</td>
<td>GE</td>
<td>65.9</td>
<td>67.2</td>
<td>0.005</td>
<td>14.4</td>
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<tr>
<td></td>
<td>PE</td>
<td>87.3</td>
<td>92.0</td>
<td>0.032</td>
<td>14.9</td>
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<tr>
<td>Capital liberalization</td>
<td>GE</td>
<td>42.1</td>
<td>32.8</td>
<td>0.025</td>
<td>5.6</td>
</tr>
<tr>
<td></td>
<td>PE</td>
<td>34.3</td>
<td>26.5</td>
<td>0.019</td>
<td>1.6</td>
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<tr>
<td>Bank expansion</td>
<td>GE</td>
<td>24.0</td>
<td>24.9</td>
<td>-0.006</td>
<td>7.0</td>
</tr>
<tr>
<td></td>
<td>PE</td>
<td>52.2</td>
<td>56.3</td>
<td>0.011</td>
<td>7.4</td>
</tr>
<tr>
<td>No reforms</td>
<td>GE</td>
<td>4.2</td>
<td>5.7</td>
<td>0.003</td>
<td>-0.5</td>
</tr>
<tr>
<td></td>
<td>PE</td>
<td>4.3</td>
<td>5.4</td>
<td>0.002</td>
<td>-0.5</td>
</tr>
</tbody>
</table>

Note: In this table, we report the change in welfare, GDP, income inequality, and credit access conditions between 1986-1996 due to various policies in partial equilibrium and general equilibrium, respectively. The baseline simulation considers all reforms happened during this period together. The capital liberalization counterfactual simulates the reform with capital inflows and lower interest rate spread by fixing the number of commercial banks and BAAC at their initial values in 1986. The bank expansion counterfactual simulates the expansion of commercial banks and BAAC by fixing the interest rate spread and capital flows at their initial values in 1986. For each counterfactual simulation, we consider both general equilibrium with endogenously determined deposit rates and wages, and partial equilibrium in which deposit rates and wages are fixed at their initial values in 1986. All the variables of interest are calculated using their 1986 values as reference points. The welfare column reports the percent change in average welfare between 1986-1996. The GDP column reports the percent change in GDP between 1986-1996. The income Gini column reports the arithmetic difference in income Gini coefficient between 1986-1996. The columns for credit access ratio and credit access Gini report the arithmetic difference in credit access ratio and Gini coefficient between 1986-1996.
Table 4: Sensitivity analysis of the credit provision and deposit mobilization channels.

<table>
<thead>
<tr>
<th>Channel</th>
<th>Increase in capital demand</th>
<th>% contribution in GDP growth</th>
<th>Benchmark ( \kappa = 0.45, s = 0.0051 )</th>
<th>Higher ( \kappa = 0.8 )</th>
<th>Higher ( s = 0.01 )</th>
</tr>
</thead>
<tbody>
<tr>
<td>Credit provision</td>
<td>Increase in capital demand</td>
<td>42%</td>
<td>44%</td>
<td>41%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>% contribution in GDP growth</td>
<td>68%</td>
<td>80%</td>
<td>63%</td>
<td></td>
</tr>
<tr>
<td>Deposit mobilization</td>
<td>Increase in capital supply</td>
<td>7%</td>
<td>7%</td>
<td>10%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>% contribution in GDP growth</td>
<td>48%</td>
<td>32%</td>
<td>59%</td>
<td></td>
</tr>
</tbody>
</table>

Note: In this table, we report the contribution of the credit provision and the deposit mobilization channel to the increase in GDP caused by bank expansion between 1986-1996. We compute the % contribution in GDP growth for credit provision as the ratio of the cumulative GDP growth between 1986-1996 caused by the credit provision channel alone and by bank expansion (For example, for the benchmark case, the number 68% is obtained from \( \frac{17}{25} = 68\% \)). Similarly, we compute the % contribution in GDP growth for deposit mobilization using the cumulative GDP growth caused by the channel deposit mobilization alone. We also report the increase in capital demand in partial equilibrium (i.e., interest rates and wages are fixed at the 1986 level) caused by the channel of credit provision and the increase in capital supply caused by the channel of deposit mobilization between 1986-1996. Column 1 reports the benchmark case based on the calibrated parameters in Table 2. Column 2 reports the simulation results with higher initial inequality in credit entry costs, \( \kappa = 0.8 \) and column 3 reports the simulation results with higher initial inequality in transaction costs, \( s = 0.01 \).
Appendix

A Supplemental Information on Data

A.1 Road types

We estimate the average car travel speed for different types of roads in Thailand using GIS (see Table E.1). The speed information is used to estimate the car travel time along the road network between each pair of markets. For villages that are not located on any road, we assign them to the nearest road and calculate travel time based on the traveling speed of footpath, 15 km/hour.

A.2 Branch Locations

We obtain the village/tambon/municipal name of each branch location using Google map API. For those branches that can be matched directly to any village, the village’s location, which is represented as point data in the GIS system, is used to proxy the branch’s location. Branches that cannot be matched at the village level are matched to tambons and/or municipal districts (both are geo-units represented as polygon areas in the GIS system). They are assigned to road network intersections according to the following procedures:

(i) For each branch, find the region within which the branch is located. In particular, if the branch is mapped to either a tambon or a municipal district, the polygon area of the tambon or the municipal district is considered as the associated region. If the branch is mapped to both a tambon and a municipal district, the overlapping area of the two polygons is considered as the associated region.

(ii) For the entire economy, find all the road intersections.

(iii) For each intersection, find all the roads that are connected to it. We assign a weight to each type of road as eight minus the road’s code number (see Table E.1). Thus, for example, the highest level of road with code 1, has the highest weight 7. The weight of each intersection is calculated as the sum of all connecting roads’ weights. The weights represent the relative importance of intersections in terms of connecting major roads.

(iv) For each region defined in step (i), find all the branches that are belonged to the region. The location of the first branch opened in this region is assigned to the intersection with the highest weight, and the location of the second opened branch is assigned to the intersection with the second highest weight, and so on. We also require the branches opened by the same bank to be at least 500 meters apart from each other.

B Numerical Algorithm

In this appendix section, we present the numerical algorithm. In subsection B.1, we present the main algorithm that solves our model. As we discuss in section 5, the main algorithm includes approximations
of the bank’s branch opening decisions and the agent’s utility maximization problem. The latter is implemented in three stages. In stage 1, the agents’ problem is solved by setting $\omega = 0.25$ in the Cobb-Douglas utility function. In stage 2, the agents’ problem is solved using calibrated state-dependent $\omega(b, z, d)$. In stage 3, the agents’ problem is solved using calibrated time-varying and market specific $\omega_t(b, z, n)$. In subsection B.2, we present the algorithm that solves $\omega$s in stage 2 and stage 3.

**B.1 Main Algorithm**

The hardware we use to solve the model is a 32-core server, Dell PowerEdge R910. The main code is written in Matlab and the computationally intensive parts (including computing the evolution of distributions and the choice of branch locations) are written in C++ with parallelization. The number of wealth grids is set to be 500 on the support $[0, 10]$. We use 250 evenly divided wealth grids on $[0, 1]$ and $[1, 10]$, respectively, as the nonlinearity is large when wealth is small. The Pareto distribution is truncated at the value corresponding to the 99.5% cumulative distribution function. The number of talent grids is 20, evenly distributed on the support of the truncated Pareto distribution.

Starting in period $t_0 = 0$, we solve the problem in the following steps.

**INITIALIZATION**

1. Consider period $t = t_0$. Initialize the bank’s branch locations in period $t$ using the bank’s branch locations in period $t - 1$ (i.e., no expansion).

**BANK EXPANSION**

2. Using the following subroutine to find the most profitable unbanked location $n^*$ for opening a branch. For each market $n_0$ not yet having a branch in period $t$, suppose that a branch is opened, then:
   
   (a) Compute the credit entry costs $\tilde{\phi}^{n}(n_0)$ and transaction costs $\tilde{\xi}^{n}(n_0)$ in each market $n$.
   (b) Guess the interest rate $\tilde{w}_t(n_0)$ using the bisection method.
   (c) Guess the wage $\tilde{r}_t(n_0)$ using the bisection method.
   (d) For each pair of $(b, z)$ in each market $n$, solve agents’ working-period problem (4.3-4.6) to maximize income, and obtain $\tilde{h}^{n}_t(b, z; n_0)$, $\tilde{g}^{n}_t(b, z; n_0)$, $\tilde{k}^{n}_t(b, z; n_0)$, and $\tilde{l}^{n}_t(b, z; n_0)$.
   (e) For each pair of $(b, z)$ in each market $n$, solve agents’ leisure-period problem (5.2) to maximize utility, and obtain $\tilde{c}^{n}_t(b, z; n_0)$, $\tilde{N}^{n}_t(b, z; n_0)$, and $\tilde{m}^{n}_t(b, z; n_0)$.
   (f) Compute aggregate capital supply and demand using distributions $h^{n}_t(b, z)_1$ and $h^{n}_t(b, z)_2$ and the computed policy functions. Check the capital market clearing condition (4.17).
      - If it is satisfied, go to step (g); otherwise, go to step (c).
   (g) Compute aggregate labor supply and demand using distributions $h^{n}_t(b, z)_1$ and $h^{n}_t(b, z)_2$ and the computed policy functions. Check the capital market clearing condition (4.18).
      - If it is satisfied, go to step (h); otherwise, go to step (b).

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39Problem (5.2) is solved using different $\omega$s in different stages of our approximation algorithm. The values of $\omega$ are chosen according to Appendix B.2.
(h) Compute the bank’s profit $\hat{\Pi}_t(n_0)$ using equation (4.14).

(3). Open a branch at $n^* = \arg\max_{n_0} \hat{\Pi}_t(n_0)$ in period $t$.

(4). Repeat steps (2) – (3) $y_t$ times, so that $y_t$ branches are opened by the bank in period $t$.

**TRANSITION TO $t + 1$**

(5). Based on the policy functions and equilibrium prices computed in the last iteration of step (3), using equation (4.19) to compute the joint distribution of agents’ wealth and talent in each market $n$ in period $t + 1$.

(6). Set $t_0 = t_0 + 1$, and go to step (1).

**B.2 Algorithm for Savings Rates Approximation**

In this subsection, we present the algorithm that calibrates parameter values and the heterogeneous $\omega$s in stage 2 and 3.

**B.2.1 Stage-2**

(1). Guess the average equilibrium interest rate $\bar{r}$ and wage $\bar{w}$ between 1986-1996, and the values of parameters $\gamma, s, \eta, \kappa, f_0, \rho, q_w, \beta$. The initial guess uses values from stage-1 simulation.

(2). For each grid of talent $z$, wealth $b$, and travel time $d^{40}$, we solve problem (4.11) to obtain the savings rates, $\bar{s}(b, z, d)$. Note that the travel time affects the entrepreneurs’ profit $\mu_c$ and the transaction fee $\zeta$ in problem (4.11). For each $d$, we initialize the value functions using $V(b, z) = b^{1-\sigma} - \sigma b^{1-\sigma}$, and do 40 iterations to get convergence in $V(b, z)$.

(3). Calculate $\omega(b, z, d)$ using formula (5.5).

(4). Calibrate parameters $\gamma, s, \eta, \kappa, f_0, \rho, q_w, \beta$ to match the moments presented in section 6. In this step, the model needs to be solved multiple times in order to match the moments. When solving the model, implement the main algorithm in subsection B.1 with step (e) being executed using $\omega(b, z, d)$ for agents of type $(b, z)$ living in a market whose current travel time to the nearest bank branch is $d$.

(5). Check if the calibrated parameters $\hat{\gamma}, \hat{s}, \hat{\eta}, \hat{\kappa}, \hat{f}_0, \hat{\rho}, \hat{q}_w, \hat{\beta}$ and the new average equilibrium prices $\bar{r}', \bar{w}'$, match the guess in step (1). If not, go to step (1) and form a new guess.

**B.2.2 Stage-3**

(1). Guess the equilibrium prices $\{r_t, w_t\}_{t=10}^{t=T}$, bank locations $\{\Xi_t\}_{t=10}^{t=T}$, and the values of parameters $\gamma, s, \eta, \kappa, f_0, \rho, q_w, \beta$. The bank locations, capital flows, and interest rate spreads between $t = 10$ and $t = T$ are fixed at the values at $t = 10$. The initial guess uses values from stage-2 simulation. The simulation period in stage 1 and stage 2 is from $t = 0$ to $t = 10$, corresponding to the period between 1986-1996. In stage 3, we set $T = 50$ to ensure that the model economy will eventually reach the steady state.

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\(^{40}\)We use 400 grids for travel time between 0 and 200 minutes. The grid length is 0.2 minute on $[0, 50]$, and 1 minute on $[51, 200]$. 79
(2). In each market, we solve the value functions of problem (4.11) in steady state, \( V_T(b, z; n) \), based on the steady-state prices \( \{r_T, w_T\} \) and the branch locations at \( t = 10 \). We conduct 40 iterations to get convergence in \( V_T(b, z; n) \).

(3). Solve the value functions \( \{V_t(b, z; n)\}_{t=0}^{T-1} \) and the savings rates \( \{s_t(b, z; n)\}_{t=0}^{T-1} \) of problem (4.11) by doing backward induction.

(4). Calculate \( \omega_t(b, z; n) \) using a formula similar to (5.5).

(5). Calibrate parameters \( \gamma, s, \eta, \kappa, f_0, \rho, q_w, \beta \) to match the moments presented in section 6. In this step, the model needs to be solved multiple times in order to match the moments. When solving the model, implement the main algorithm in subsection B.1 with step (e) being executed using \( \omega_t(b, z; n) \) for agents of type \( (b, z) \) living in market \( n \).

(6). Check if the calibrated parameters \( \hat{\gamma}, \hat{s}, \hat{\eta}, \hat{\kappa}, \hat{f}_0, \hat{\rho}, \hat{q}_w, \hat{\beta} \) and the new equilibrium prices \( \{r'_t, w'_t\}_{t=0}^{T} \), bank locations \( \{\Xi'_t\}_{t=0}^{10} \), match the guess in step (1). If not, go to step (1) and form a new guess.

C Thai Financial Crisis

In this section, we check how the model performs after 1996, during the Thai financial crisis. Figure E.1 shows that our model predicts a larger drop in GDP during the Thai financial crisis 1997-1999. This is mainly caused by the withdraw of capital flows from 10% of GDP to 9% of GDP.

D Evaluation of the Goodness of Approximation

In this appendix section, we assess the goodness of the approximation algorithm that solves the bank’s branch opening decisions detailed in subsection 5.1.

We conduct two semi-forward-looking experiments. In one experiment, we assume that the bank considers the information on future prices, distributions, and BAAC branch locations when choosing branch locations. In the other experiment, we assume that the bank not only considers the information in future periods but also its own actions in future periods when choosing branch locations. Because the second experiment involves solving an NP-hard combinatorial programming problem, we only solve the problems for provinces with a relatively small number of markets. We find that anticipating future prices, distributions, and BAAC branch locations would have little effect on the bank’s branch opening decisions. Anticipating the bank’s own action would have limited effect on the branch opening decisions in most provinces, but in some provinces, there is a relatively large difference.

D.1 Experiment 1

In the first experiment, we allow the bank to anticipate the equilibrium wage, interest rate, wealth distribution, and BAAC branch locations that would happen in the future when choosing branch locations. However, for tractability, we do not solve these equilibrium objects, instead we set their values according to the baseline simulation in section 6.2.
In this experiment, the bank is pseudo forward looking in the sense that it does not anticipate its own branch opening decisions in the future, from period $t + 1$ to period $T + 1$, when opening branches in period $t$. Therefore, the bank essentially maximizes (4.15) by choosing branch locations in period $t$, conditional on no future branch openings. By comparing the resulting branch opening decisions with our baseline simulation, this experiment checks how anticipation of future economic environment would change the branch locations.

Panel A of Figure E.2 plots the histogram for the difference in branch opening time between the bank in this experiment and the bank in our baseline approximation. It shows that in most locations, branch opening times are exactly consistent in the two simulations. In panel B, we report the histogram for the absolute discrepancy in branch opening time, averaged at the provincial level. In most provinces, the average discrepancy is smaller than 0.5 years.

Figure E.3 further illustrates that the small difference in branch opening decisions is mainly due to the anticipation of future BAAC locations. In Panel A, we allow the bank to anticipate future BAAC locations, but not equilibrium prices and distributions.\(^{41}\) In Panel B, we allow the bank to anticipate future equilibrium prices and distributions but not BAAC locations. The comparison shows that the major difference in branch opening decisions between the bank in experiment 1 and the bank in our baseline approximation is caused by future BAAC locations. The bank anticipating future BAAC locations is less likely to open a branch in a market if that market will be occupied by a BAAC branch in the near future, since half of the savings would be collected by the BAAC branch. By contrast, the bank in our baseline approximation may choose to open a branch there if the market generates highest profit in the current period.

In principle, whether BAAC branch locations could be anticipated should have a large effect on the bank’s decision. However, this does not happen in our model because as argued by Assuncao, Mityakovy and Townsend (2012), BAAC and commercial banks presumably target different markets in Thailand. BAAC tends to open branches in rural regions to maximize financial access ratio, while commercial banks open branches in wealthy and populous regions to maximize profit.

Panel B implies that anticipating future equilibrium prices and distributions does not play a big role. Intuitively, the equilibrium prices would not have a big impact on branch choice since they arguably affect all markets altogether instead of making some markets more favorable for branch expansion.

### D.2 Experiment 2

In this experiment, we allow the bank to anticipate both the future economic environment as it does in the first experiment, and the impact of its own future actions on the change of savings. That is, we consider a fully forward-looking bank making branch opening decisions. However, as we discuss in section 5, the optimal branch opening decisions are solutions to an NP-hard combinatorial programming problem, which is tractable only when the decision space is small. Therefore, we conduct our second experiment at the provincial level. Specifically, we solve the branch opening decisions for each province separately.

\(^{41}\)We assume that the bank uses the equilibrium prices and distributions in current period for all future periods when calculating profit.
while taking branches in other provinces as given. Then, we compare the difference in predicted branch locations between the bank in this experiment and the bank in our baseline approximation.

However, even at the provincial level, the problem is not tractable for some provinces due to the large number of possible combinations (see Table E.2). We therefore restrict our comparison to the 49 provinces with less than 1 million possible combinations. Figure E.4 presents the results. Panel A plots the histogram for the absolute discrepancy in branch opening time, averaged at the provincial level. It shows that anticipating the bank’s own future branch openings does change the branch opening decisions in some markets. Our baseline approximation does not generate a very different prediction, because more than 60% of the provinces have the average discrepancy below 1 year.

Next we investigate whether the small difference in branch opening decisions between the bank in experiment 2 and the bank in our baseline approximation is driven by selection biases. The concern here is that we are only able to compute relatively small provinces with fewer than 1 million combinations. To check whether there is a systematic bias in average timing discrepancy, we plot the histogram of the number of combinations for provinces whose average timing discrepancy is less than 1 year and those with more than 1 year discrepancy, in panel B and panel C respectively. We do not detect a clear systematic bias as there are comparable big and small markets in both panels. In fact, the correlation between the number of combinations and the average timing discrepancy is -0.029, which suggests that provinces with a larger number of combinations are more likely to be better approximated by our baseline algorithm.

E Intermediate Simulation Results

In this appendix, we report the simulation results for each step of the approximation algorithm that solves the agent’s problem detailed in subsection 5.2.

TBA...
Figure E.1: GDP growth during the period 1986-1999.
Figure E.2: Comparing the difference in branch opening decisions between the bank in experiment 1 and the bank in our baseline approximation.

A. All markets

B. All provinces

Note: This figure compares the difference in branch opening time between the bank in experiment 1 and the bank in our baseline approximation. In experiment 1, we allow the bank to anticipate the equilibrium wage, interest rate, wealth distribution, and BAAC branch locations that would happen in the future when choosing branch locations. Panel A plots the histogram of the difference in branch opening time between the bank in experiment 1 and the bank in our baseline approximation. It shows that in most locations, branch opening times are exactly consistent in the two simulations. Panel B plots the histogram of the absolute discrepancy in branch opening time, averaged at the provincial level. In most provinces, the average discrepancy is smaller than 0.5 years.

Figure E.3: Comparing the difference in branch opening decisions between the bank in experiment 1 (two sub-experiment) and the bank in our baseline approximation.

A. Anticipate BAAC

B. Anticipate prices and distributions

Note: This figure separately considers the role of anticipating future BAAC locations and future equilibrium wage, interest rate, and wealth distribution. Panel A plots the histogram of the absolute discrepancy in branch opening time, averaged at the provincial level, between the bank anticipating future BAAC locations and the bank in our baseline approximation. Panel B plots the histogram of the absolute discrepancy in branch opening time, averaged at the provincial level, between the bank anticipating future equilibrium wage, interest rate, and wealth distribution and the bank in our baseline approximation.
Figure E.4: Comparing the difference in branch opening decisions between the bank in experiment 2 and the bank in our baseline approximation.
Table E.1: Road type and the estimated average car travel speed

<table>
<thead>
<tr>
<th>Code</th>
<th>Road type</th>
<th>Average speed (km/hour)</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>All weather: hard surface, two or more lanes wide</td>
<td>45</td>
</tr>
<tr>
<td>2</td>
<td>All weather: loose or light surface, two or more lanes wide</td>
<td>38</td>
</tr>
<tr>
<td>3</td>
<td>All weather: hard surface, one lane wide</td>
<td>38</td>
</tr>
<tr>
<td>4</td>
<td>All weather: loose or light surface, one lane wide</td>
<td>30</td>
</tr>
<tr>
<td>5</td>
<td>Fair or dry weather: loose surface</td>
<td>25</td>
</tr>
<tr>
<td>6</td>
<td>Cart track</td>
<td>20</td>
</tr>
<tr>
<td>7</td>
<td>Footpath, trail</td>
<td>15</td>
</tr>
</tbody>
</table>

Table E.2: The number of combinations at provincial level

<table>
<thead>
<tr>
<th>Num. of combinations</th>
<th>Num. of provinces</th>
</tr>
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<tbody>
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<td>&lt;100</td>
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</tr>
<tr>
<td>&lt;10^3</td>
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</tr>
<tr>
<td>&lt;10^15</td>
<td>73</td>
</tr>
<tr>
<td>&lt;10^17</td>
<td>75</td>
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