Scaling Up Financial Interventions in Space*

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Abstract

What are the effects of scaling up financial interventions in space? We investigate this question in the context of Thailand's 'Million Baht Village Fund' program, using quasi-natural variation in credit per household at the village level and an extensive administrative village census. We find significant village-level impacts of credit and credit spillovers to neighboring villages. Credit spillovers dominate the direct effects, where heterogeneity in credit spillovers is a function of the local spatial configuration of villages. We find that migration between villages rather than trade or capital flows is the primary source of spillovers. We develop a dynamic spatial model with migration to interpret and explain the spatial and general equilibrium effects we find in the data. Model predictions align with the empirical results and suggest uneven welfare gains by wealth and agent type. Spatial spillovers generate welfare trade-offs between occupations, raising wages to benefit workers and at a cost to entrepreneurs. Counterfactual distribution of credit minimizes entrepreneur-worker trade-offs and yields welfare gains over the actual intervention.

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1 Introduction

What are the effects of scaling up financial interventions in space? Interventions are often designed, tested, and operated locally, village by village. Yet to gauge the impact such policies would have at scale, it is necessary to postulate how spatial and financial frictions interact.

We investigate this question in the context of Thailand's 'Million Baht Village Fund' program. The Village Fund program, run by Thailand's government, provided a seed grant of 1 million Baht (∼$26,000) per village to create a village savings and loans fund in 2002. Each fund provided micro-loans to entrepreneurs living within the village. Our setting is unusual because the policy shift was introduced at full scale from the get-go – the funds were allocated to every village in Thailand. By leveraging quasi-natural variation in credit per capita and combining a comprehensive village-level administrative census with GIS data and the Townsend Thai data, we can directly observe the spatial and general equilibrium impacts in 40,000 Thai villages and infer the frictions and channels from these data. Specifically, the observed patterns motivate, inform, and validate our chosen model, which we then use to interpret the aggregate and distributional impacts of the program.

Our approach contrasts with an emerging literature that uses models to predict the macro-impacts of experimental policy (see Buera, Kaboski, and Townsend 2022 for a review). Typically, predicting general equilibrium effects requires taking an a priori stance on the key channels and frictions, even when the model is calibrated to partial equilibrium results from field experiments. For instance, in studying the distributional effects of financial frictions, Buera, Kaboski, and Shin (2021) assume frictionless labor and goods markets, whereas Berquist et al (2022) feature trade costs in order to predict the aggregate impacts of input subsidies. In contrast, we observe the general equilibrium effects and mechanisms and estimate the frictions ex-post.

The data we use display economically and statistically significant spatial and general equilibrium effects. We document four facts: (1) wages increased in credit per capita, (2) wages increased in the credit per capita of neighboring (<5km) villages, (3) wages increased more in credit per capita when the villages were more isolated, and (4) net migration increased in credit per capita, whereas we do not find that either trade or capital flows responded to the Village Fund. Our within-village estimates of credit on wages are consistent with previous research documenting the within-village general equilibrium effects of financial interventions (e.g., Kaboski and Townsend (2011, 2012), Buera, Kaboski, and Shin (2018, 2021), Breza and Kinnan (2022)). We depart from this literature in our focus on the spatial equilibrium and investigate the role of migration in propagating and mediating impacts.

To understand the incidence of financial interventions across villages, we exposit a dynamic multi-village model with forward-looking entrepreneurs and workers. Entrepreneurs permanently reside in the village where they are born, making consumption and savings decisions while operating firms using capital and labor. Entrepreneurs are heterogeneous in TFP and assets across villages and are limited in how much capital to employ by a collateral constraint. Workers, in contrast, can migrate across villages, making asset and location decisions and paying migration costs out of accumulated wealth. They earn wages by providing one unit of inelastic labor to firms in their village of residence.

In constructing our model, we build on a wealth of knowledge on the structure of village economies. By taking advantage of what has been learned previous studies of the 'Village Fund', we can emphasize the key dimensions of the village environment. For instance, we do not incorporate occupation choice into the worker's problem, as previous research has found no statistically significant impact of credit expansion on occupation choice. Additionally, the provision of labor is inelastic because previous estimates of the labor elasticity in the Townsend Thai data are small and insignificant. Elements of the spatial environment also draw on previous research. For example, our model features frictionless spatial capital markets as Paweenawat and Townsend (2018) find that village interest rates converge to a common national rate in the late 90's and early 2000's. We discuss these and other modeling decisions in Section 3 in more detail.

Our model achieves tractability despite extending the migration framework of Artuc et al. (2010), Caliendo, Dvorkin, Parro (2018), and Balboni (2021) to incorporate asset choice and pecuniary migration costs. Most quantitative spatial models are static, while dynamic ones do not feature intertemporal choices (e.g., saving) other than migration in the problem of the migrating agents[1]. The critical assumption that gives us tractability is the timing of events: workers must choose future assets before knowing the idiosyncratic location shocks[2]. We further reduce the dimensionality of our model by constructing a pseudo map with fewer villages, adapting Gaubert (2018)'s approach of modeling heterogeneous locations along a line to modeling villages along the circumference of a circle. We then calibrate the location of villages on the circle using judiciously chosen summary statistics that match the actual village geography. We can thus simulate the overall structural model based on a constructed pseudo map and have a good approximation of what we would do if we could simulate the

[1]For example, Kleinman, Liu, and Redding (2022) develop a dynamic multi-location model with endogenous capital accumulation where immobile landlords make asset decisions, but migrant workers cannot save or borrow. On the other hand, Lagakos, Mobarak, Waugh (2020) and Morten (2019) allow workers to make intertemporal choices other than migration but only feature two locations.

[2]Ji, Song, and Townsend (2021) adopt this approach to study the spatial impact of bank branch locations. However, migration costs in their model are constant and the destination location is random, unlike in this paper where we allow costs to vary with distance and migration flows are endogenously determined.

model with all 40,000 villages.

We discipline our model to match Thailand's economy pre-intervention. We draw most parameters from previous work with the Townsend Thai data or in similar settings in developing countries. We internally calibrate the migration cost as a function of distance, matching pre-intervention cross-sectional distributions of wages and populations. The Village Fund intervention is then modeled as a relaxation of firm borrowing constraints.

Qualitatively, the model predictions are in line with empirical results. As in the data, we find that the model simulated village fund generated 1) a positive wage increase, 2) a positive wage spillover, 3) larger spillovers than direct effects, and 4) a positive increase in populations. Quantitatively, the elasticities are also similar (within 2-3$\times$ of each other). We do not expect the elasticities to match precisely, as they are an un-targeted moment in the calibration. Their similarity, qualitatively and quantitatively, provides a key test of model validity.

We then focus on the distributional impacts of the Village Fund. First, there is heterogeneity in treatment effects by wealth. Workers are constrained along two dimensions: a borrowing constraint and a pecuniary migration cost. Changes in the wage have heterogeneous effects by wealth because the constraints bind at different points in the wealth distribution. Small wage changes relax the migration constraint for the rich and the borrowing constraint for the poor. Large wage changes similarly relax the migration constraint for the wealthy, but relax both the migration and borrowing constraint for the poor. When the change in wages is small, welfare inequality increases because the wealthy benefit more than the poor.

There is also treatment heterogeneity by occupation. While worker welfare increases, entrepreneur welfare decreases. Migration generates this welfare trade-off. Within a village, relaxed credit constraints allow entrepreneurs to increase capital usage, and the increased demand for capital increases the demand for labor. This benefits entrepreneurs by increasing profits and benefits workers by increasing wages. Spatial spillovers have the opposite effect. Migration into highly treated villages induces higher wages in the villages left behind, which helps workers but hurts entrepreneurs who receive less credit and face rising wages. Counterfactual credit distributions generate larger welfare gains for entrepreneurs by minimizing spillovers that generate unequal capital deepening across villages.

Our paper is structured as follows. Section 2 discusses the setting, empirical approach, and findings. In Section 3, we develop a model and discuss the results and counterfactuals. Section 4 concludes.

2 Empirical Results

2.1 Quasi-Experimental Design of the Program

We take advantage of two elements of the program to implement our research design. One, the program was unexpected. The Village Fund was the campaign promise of Prime Minister Thaksin Shinawatra of the Thai Rak Thai party, the underdog of the 2001 general election. Such a policy would have been unthinkable under the previous administration, the Democrat party, which was known for its frugality. Yet despite a strong showing in 1996, the Democrat party flailed in the next election. After the change in leadership in 2001, the program was quickly implemented. Koboski and Townsend (2012) document that, by the end of 2002, most villages in their sample had received seed funding and had loaned out almost the entire amount.

Two, each bank was endowed with 1 million Baht (around $26,000) regardless of the size of the village, resulting in quasi-natural variation in credit per household at the village level. There are strong a priori reasons for expecting this variation in inverse village size to be exogenous with respect to the variables of interest[3]. First, in the 1990s, villages were often divided and redistricted for administrative purposes. Competition between various government agencies generated seemingly random redistricting of villages. Although such redistricting calmed down under the new administration, at the time the Village Fund was implemented, village size was often determined through local geopolitics rather than economic or geographic forces. Second, most of the variation generated by inverse village size is for small villages - credit per capita tapers off at zero for large villages. Our analysis, therefore, depends on comparisons between small villages rather than between urban and rural areas. We should not be picking up differences in urban and rural policy and control for variation in policy at various geopolitical sub-units (provinces, amphoes, and districts). Third, extensive analysis by Kaboski and Townsend 2012 shows that village size is neither spatially auto-correlated nor correlated with underlying geographic features like roads or rivers. Geographic features explain at most 5 percent of the variation in village size. Fourth, we verify in Section 2 that inverse village size is unrelated to the variables of interest in the years prior to the program by introducing interactions of the inverse village size variable with the pre-program years. We find that year-specific village-size interactions do not significantly predict outcomes before the program.

[3]Suarez, Serrato, and Wingender (2016) similarly use inverse population size as an instrument to gauge the impact of government programs that are tied to US census population counts. Since the US Census is done only once every decade, population levels are inaccurate at the time of policy implementation or funding allocation, generating exogenous variation in funding per capita.

2.2 Data

Our primary data source is Thailand's Community Development Department (CDD) panel, a bi-annual longitudinal administrative census following economic conditions in rural Thailand for over 60,000 villages and spanning both pre- and post-program years from 1986 to 2009. To create a balanced panel, we harmonize the data across years and narrow our sample to $40,000$ villages existing in all years of our sample. Village headmen are surveyed bi-annually on the economic conditions in their village. The key variables for our analysis are village wages and populations. Village wages are reported as the average daily wage received by workers at the time of the survey. The population is reported as the number of households.

We combine the CDD with GIS data of village locations and Thailand's road network, which we use to identify neighboring villages. Villages are densely located, often mere steps away. We show in Figure 1 and Figure 2 the distributions of distance to the nearest village and the number of villages within 5km., respectively. The vast majority of villages are located within 5km of another village and, on average, have 20 neighboring villages within that distance.

Figure 1: Distance to Nearest Village

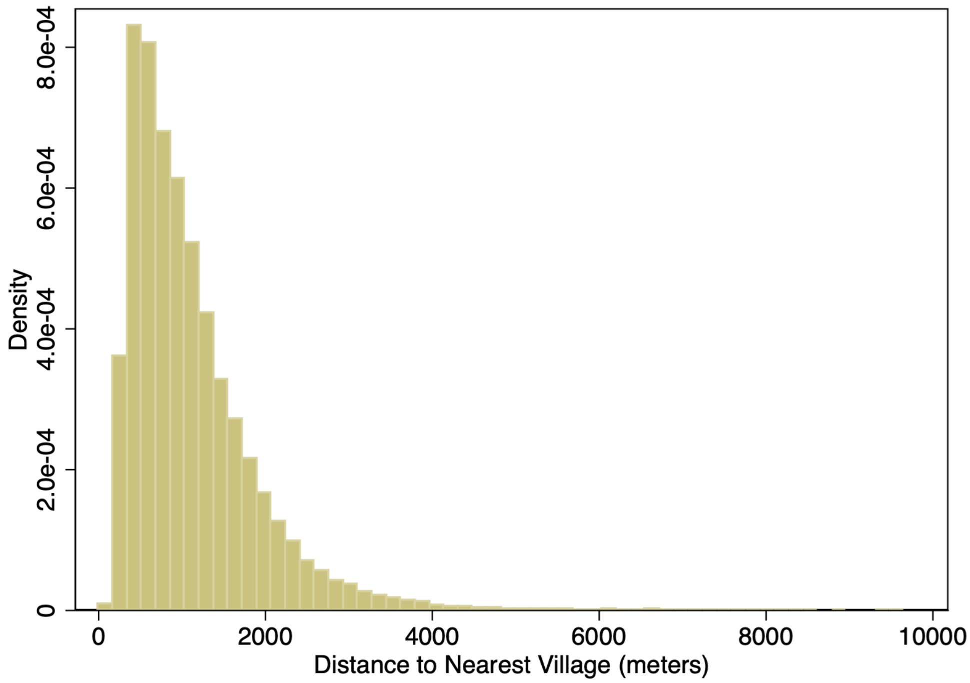
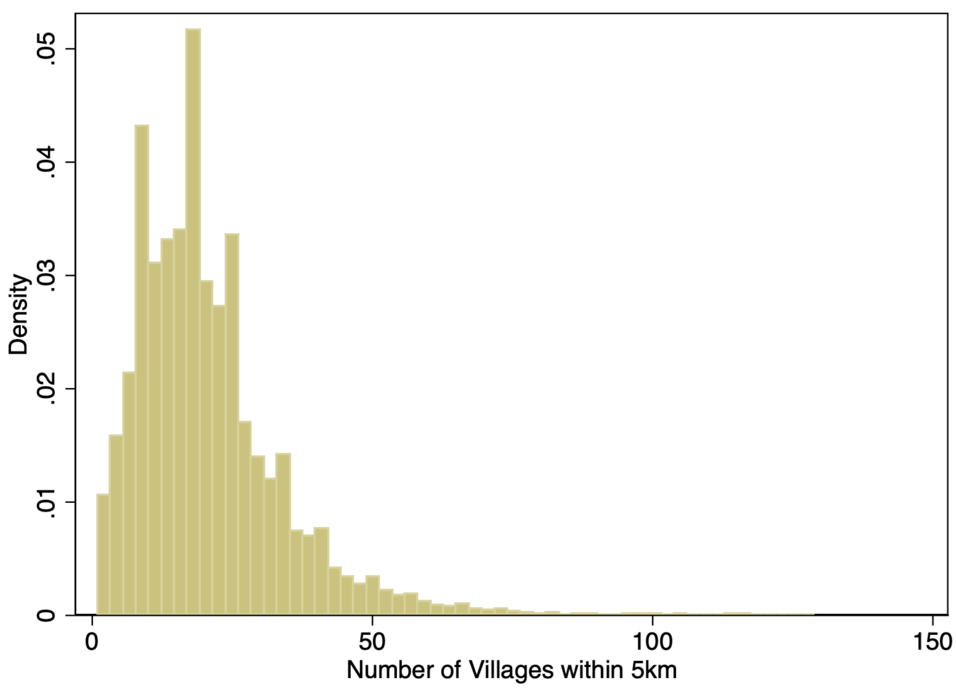


Figure 2: Number of Villages Within 5 km



We further supplement the CDD with the Townsend Thai panel. We use the Townsend Thai panel for two purposes. First, although the Townsend Thai panel has a smaller sample

(64 villages) than the CDD, it provides additional evidence on various channels through which villages are linked and spatial spillovers operate (e.g., trade, capital flows). The Townsend Thai data measures these variables through household surveys, which allows aggregation up to the village level. Second, we use the Townsend Thai panel to assess the accuracy of the wages reported in the CDD. We find a strong positive correlation between wages in the CDD and the Townsend Thai Data. We describe the exercise in greater detail in appendix B.1.

2.3 Spatial and General Equilibrium Effects

We document four facts about the spatial and general equilibrium effects of the 'Village Fund'.

Fact 1 (Direct effect of credit). *Controlling for year and location fixed effects, the wage is increasing in credit per capita.*

We establish Fact 1 by running the regression

$$y_{it} = \beta \text{Credit}_i * \text{Post}_t + \phi_i + \phi_t + \epsilon_{it} \tag{1}$$

where y_{it} is the outcome variable (wages, populations) in village i at time t; ϕ_{it} is the village-year fixed effect; Credit_i is equivalent to $100/NoHouseholds_{i,2001}$, the inverse of the number of households in village i in 2001, interpreted as credit infusion per household in 10,000s of baht; Post_t is a dummy equal to 1 if $t \geq 2003$, the first year in the CDD data for which the program is in effect; and ϵ_{it} is an error term.

We show the results in Table 1 column 1. Increased credit per capita has both an economically and statistically significant effect on daily wages[4]. An increase in $10,000$ baht per capita provided to the villages increases the daily wage by 1%[5]. To put the magnitudes in perspective, the median village has a population of just over 100 households, implying a wage increase of 1%; however, the wage increases by 5% in a village with 20 households[6]. An

[4]The key identification concern is that different-sized villages have different trends in wages. If smaller villages were to have faster wage growth than larger villages pre-program, then any estimated effects post-program could be due to wage trends rather than per capita credit infusion. We find that inverse population size does not significantly predict outcomes before the program, satisfying our assumption of parallel trends. See appendix B.2 for additional details about identification.

[5]The results are robust to various specifications, including using wage levels instead of changes and controlling for various geopolitical sub-units. See appendix B.2 for a full list of robustness checks.

[6]The treatment effect is smaller than that found in a similar regression run by Kaboski and Townsend (2012), who find a 6% increase in wages for every $10,000$ baht per capita. The difference is, in part, mechanical. First, Kaboski and Townsend (2012) find positive effects on construction and business wages but no effect on agricultural wages. Since the CDD does not disaggregate the wage by sector, the wage variable is a composite of wages in various sectors. Second, Kaboski and Townsend (2012) focus their analysis on the smallest villages for whom the effect is most potent. Since we include the entire sample of villages in our analysis, it is natural to expect the overall effect to be smaller. The effect is significant at the

effect of credit on village wages suggests intra-village general equilibrium effects. Although not all households or entrepreneurs borrow from the Village Fund, the wage increase impacts all workers within a village. We attribute the wage increase to a relaxation of firms' financial constraints. The provision of additional credit relaxes the financial constraints of firms and entrepreneurs, increasing their capital and labor demand. This is consistent with Banerjee and Townsend 2011 documenting a long-run increase in firm investment and capital stock due to the 'Village Fund'[7].

Fact 2 (Spillover effects of credit). *Controlling for year and location fixed effects, the wage is increasing in the credit per capita of neighboring villages.*

We establish Fact 2 by extending the previous specification to

$$y_{it} = \beta \text{Credit}_i * \text{Post}_t + \gamma \text{NeighborCredit}_{r,i} * \text{Post}_t + \phi_i + \phi_t + \epsilon_{it} \tag{2}$$

where $\text{NeighborCredit}_{r,i}$ is an unweighted spatial kernel estimate of the inverse of the number of households in villages within radius r km of village i in 2001, and all other terms defined as earlier.

We show the results in Table 1 column 2. The effect of credit infusion in neighboring villages on wages is positive and statistically significant. An average increase of $\$10,000$ baht in neighboring villages results in a 4% increase in wages for the affected village[8]. The existence of credit spillovers highlights the importance of considering the policy in spatial equilibrium; village linkages may be equally, if not more, important in changing the wage distribution than within-village general equilibrium forces.

Puzzlingly, the effect of credit spillovers is larger than the direct effect of credit within a village. This is likely due to the high density of villages. Over 50% of villages are located within 1 km of another village and have at least 20 neighboring villages within five km[9].

1% level.

[7]Breza and Kinnan 2021 show that microfinance can also increase wages by affecting aggregate demand. The provision of additional credit relaxes household borrowing constraints, increasing consumption and prices of non-tradable goods and increasing local wages. We believe this is unlikely in our context for two reasons. First, although Kaboski and Townsend 2011 document a large immediate increase in consumption after the Village Fund, the increase was short term. Instead, Banerjee and Townsend 2011 find that in the long-run most credit ended up with entrepreneurs. Second, Paweenawat and Townsend (2020) document village trade and production using the Townsend Thai Panel and are unable to distinguish between non-tradable and tradable goods in the data. They find that locally almost all goods are traded in markets outside the village. The difference between our paper and Breza and Kinnan (2021) may be the unit of observation. We study villages, where local villages produce relatively homogeneous goods. In contrast, the unit of observation in Breza and Kinnan (2021) is a district where the distinction between tradable and non-tradable goods may be more critical to the analysis.

[8]The results are robust to various specifications, including using wage levels instead of changes and controlling for various geopolitical sub-units. They are also robust to different spillover distances (3 and 7 km). See Appendix B.2 for a full list of robustness checks.

[9]See figure 1 for a histogram of distances to the nearest village and figure 2 for a histogram of the number

If villages were spaced far apart, spatial frictions would prevent the interaction of financial intervention across villages. However, if there were no spatial frictions, the financial intervention should have a common effect on all villages. To resolve this question, we turn to Fact 3.

Fact 3 (Heterogeneity). *Controlling for year and location fixed effects, the direct effect of credit on wages is higher for more isolated villages.*

We establish Fact 3 by running the following regression

$$y_{it} = \beta \text{Credit}_i * \text{Post}_t + \theta \text{Credit}_i * \text{Post}_t * \text{Isol}_i + \phi_i + \phi_t + \epsilon_{it} \tag{3}$$

where Isol_i is a measure of the isolation of a village. In our preferred specification, we define isolation as a dummy if the distance to the nearest village is more than the 25th percentile[10]. We define all other terms as earlier.

We show the results in Table 1 column (3). We find that θ is positive and statistically significant, meaning a more isolated village will see a more substantial increase in wages due to credit infusion in their village than a less isolated village[11]. Fact 3 suggests a framework where spatial spillovers weaken (and spatial frictions increase) as the distance between villages increases. Greater distances between villages result in smaller spillovers of credit from others and larger within-village effects.

Facts 2 and 3 suggest a spatial framework where spatial frictions increase in the distance between villages. However, they do not speak to the types of linkages that generate the spillovers. Labor, capital, and goods markets integrate village economies. Since each could be theoretically responsible for generating the observed spatial spillovers, we test empirically for changes in each mechanism. It is essential to distinguish between mechanisms that may have different welfare implications. We determine the existence and importance of each mechanism in Fact 4.

Fact 4 (Mechanisms). *Controlling for year and location fixed effects, the population is increasing in credit per capita, but trade and financial flows do not respond to credit per capita.*

To establish Fact 4, we estimate equation 1, but with population, trade flows, and financial flows on the left-hand side of the equation.

We first estimate equation 1 using our measure of population in the CDD. We show

of villages within 5km.

[10] The results are robust to various definitions of the isolation measure, including defining isolation as the distance to the nearest village.

[11] The results are robust to various specifications, including using wage levels instead of changes and controlling for various geopolitical sub-units. They are also robust to various definitions of isolation, such the distance to the nearest village. See Appendix B.2 for a full list of robustness checks.

Table 1: General and Spatial Equilibrium Effects of Credit on Wages (Facts 1-3)

Variables	(1) Log Wages	(2) Log Wages	(3) Log Wages
$\text{Credit}_i * \text{Post}$	0.00996***	0.00853***	0.00546***
	(0.00121)	(0.00121)	(0.00180)
$\text{NeighborCredit}_{5,i} * \text{Post}$		0.0161**	
		(0.00703)	
$\text{Isol}_i * \text{Post}$			0.00593***
			(0.00166)
Observations	432,783	432,252	432,165
Number of Villages	39,628	39,579	39,569
R^2	0.906	0.906	0.906
Village FE	✓	✓	✓
Amophoe-Year FE	✓	✓	✓
Drop Outliers	✓	✓	✓

Notes. This table reports the results of estimating equations 1, 2, and 3 in columns (1), (2), and (3), respectively. Standard errors clustered at tambon-level throughout. *** p<0.01, ** p<0.05, * p<0.1

the results in Table 2 panel A. We find a positive and statistically significant effect on populations reported: an increase in $10,000$ baht per capita results in a 4% increase in populations[12]. We view this as evidence of inter-village migration. Credit injections relax local firms' borrowing constraints, raising labor demand and increasing wages. Then a higher village wage incentivizes worker immigration, increasing the village population. Commuting can also link local labor markets. This mechanism seems plausible since the spillovers are primarily local (within several km), but it cannot explain the whole story. In particular, if commuting rather than migration was responsible for the wage spillovers, populations should stay constant in response to the intervention.

We now consider and rule out trade flows as the mechanism through which the spillovers may operate. Credit injections could increase demand for goods, incentivizing production in nearby villages and increasing wages. Given iceberg trade costs, the effect on wages will attenuate with distance. Spillovers through trade would be consistent with our empirical results. We estimate equation 1 using two trade measures in the Townsend Thai Data, the trade balance and consumption imports. We report the results in Table 2 panel B. Credit per capita has no significant effect on the trade balance or consumption imports.

[12]The results are robust to various specifications, including using population levels instead of changes and controlling for various geopolitical sub-units. See Appendix B.2 for a full list of robustness checks.

Table 2: Spatial Equilibrium Mechanisms (Fact 4)

	Coefficient	Standard Error	Fixed Effects	Data Source
Panel A. Migration				
Log(Pop)	0.0313***	0.00363	✓	CDD
Panel B. Trade				
Trade Balance	-413.4	320.0	✓	Townsend Thai Data
Consumption Imports	31.59	53.73	✓	Townsend Thai Data
Panel C. Capital				
Net Factor Income Flows	-31.84	28.69	✓	Townsend Thai Data
Net Unilateral Transfers Flows	38.55	46.47	✓	Townsend Thai Data
Net Financial Asset Flows	-114.5	99.33	✓	Townsend Thai Data
Net Cash Flows	496.9	316.3	✓	Townsend Thai Data

Notes. This table reports the results of estimating equations 1 on various measures of population, trade, and financial flows. The population is measured in the CDD, while trade and financial flows are measured in the Townsend Thai Data. Standard errors in Panel A are clustered at the tambon level, and fixed effects include village and time fixed effects throughout. p-values are not adjusted for multiple hypothesis testing. *** $p<0.01$, ** $p<0.05$, * $p<0.1$

Inter-village trade is thus unlikely to account for the spatial spillovers[13]. This is consistent with our interpretation of Fact 1, where wages increase through firm investment. If wages increased through an aggregate demand channel, we should have also observed an increase in consumption imports.

Another plausible mechanism is inter-village lending and borrowing. Credit from the Village Fund increased the total amount of credit in the village, which could have been lent or gifted through informal channels to individuals in neighboring villages[14]. We can test for changes in inter-village capital flows using the Townsend Thai data by estimating equation 1 with measures of net flows of interest payments, net unilateral transfers between villages, net flows of financial assets between villages, and net flows of cash between villages as the outcome variables[15]. We show the results in Table 2 panel C. There are no significant effects on any measure of financial flows[16]. We view these results as evidence that migration rather than trade, capital, or commuting flows is the primary mechanism through which the spillovers operate.

[13] Burstein et al. (2022) point out that the effect of shocks differs between tradable and non-tradable goods, with most of the price effects accruing in the non-tradable sectors. However, Paweenawat and Townsend (2020) document village trade using the Townsend Thai Panel and cannot find any non-tradable goods in the data.

[14] The institutional setting makes direct lending of Village Funds from one village to another unlikely. The government designed credit from the Village Fund to be lent internally within the village, and the village administrative committee and the federal government closely monitored this. It is possible, however, that individuals transferred Village Funds illegally.

[15] We use levels instead of logs in the regression because many of the net flows are negative and would be dropped in the log specification. Using logs does not affect the significance of the results.

[16] The results are robust to various specifications, including different measures of population in the Townsend Thai Data. See Appendix B.2 for a full list of robustness checks.

3 Model

In this section, we present a dynamic model of migration with financial frictions. Our goal is two-fold: (i) develop a model that can address key patterns in the data and (ii) interpret the aggregate and distributional effects of scaled-up financial interventions. On the one hand, we would like to retain all the key characteristic which have been documented in village studies of financial interventions and in models of migration. On the other hand, there is a need for aggregation in order to keep things tractable. We, therefore, make a number of key simplifying assumptions that bear further discussion.

Our model is composed of the following building blocks. The economy consists of N villages (indexed by i, j). Villages are inhabited by two types of households: immobile entrepreneurs e and mobile workers w. There is a measure $L^w_{it}(a)$ of workers and $L^e_{it}(a)$ of entrepreneurs in village i and time t with assets a. An agent's occupation is determined ex-ante; there is no occupation choice margin within the model. We assume that villages produce non-differentiated goods that can be used for consumption and investment, and that agents can save and borrow through a national capital market. Villages are thus small quasi-open economies, integrated in labor and capital markets. Time is discrete and infinite horizon.

3.1 Worker Problem

The worker side of the model draws on previous work by Artuc et al (2010) and Caliendo, Dvorkin, and Parro (2018), but extends their frameworks to include asset choice and pecuniary migration costs. Workers maximize the present value of utility, discounted at rate β. They live in village i, own assets a, and provide one unit of inelastic labor in their current village at wage rate $w_{i,t}$. Workers can then either consume the wage or save it at an open economy[17] interest rate, $1 + r$. Finally, workers have the option to relocate to other villages subject to a pecuniary migration cost.

The timeline of events is as follows. At time t, a worker with assets a in village i receives wages $w_{i,t}$. The worker then chooses to save assets a' (and how much to consume), not yet knowing their idiosyncratic preference shocks for each location next period. After the realization of idiosyncratic preference shocks $\epsilon_{j,t}$ for each location, the worker chooses whether to stay or relocate to a different village j and pays the associated migration cost,

[17] Paweenawat and Townsend (2020) document a convergence in interest rates in rural Thailand to the interest rate in Bangkok. By the time of the Village Fund, there is little variation in interest rates across Thai villages.

κ_{ij}. The value function of a worker with assets a in village i at time t is

$$V_{i,t}^{w}(a) = \max_{a' \geq 0} \left\{ u\left((1+r)\,a + w_{i,t} - a'\right) + \mathrm{E}\left[\max_{j \in M(i,a')} \left\{ \beta V_{j,t+1}^{w}(a' - \kappa_{ij}) + \epsilon_{j,t} \right\} \right] \right\} \tag{4}$$

The set $M(i, a')$ is the set of all possible villages that a worker in location i and assets a' can migrate to. Although it is possible for $M = N$, it is natural to restrict M in at least two ways. First, $j \in M(i, a')$ if and only if $a' - \kappa_{ij} \geq 0$. This is a restriction on the budget constraint. The migration cost is pecuniary, meaning workers must have enough wealth to finance a move. It follows then that as a' increases, the set M expands as well. Second, one can account for geographic constraints, such as disjoint road networks.

If the idiosyncratic shocks ϵ are iid and follow a Type-I Extreme Value Distribution, we can rewrite the value function to:

$$V_{i,t}^{w}(a) = \max_{a' \geq 0} \left\{ u((1+r)a + w_{i,t} - a') + \nu \log \left(\sum_{j \in M(i,a')} \left(\exp(\beta V_{j,t+1}^{w}(a' - \kappa_{ij}))\right)^{1/\nu} \right) \right\}. \tag{5}$$

The key assumption that allows us to rewrite the value function is the timing of events: workers must choose assets a' before knowing the idiosyncratic location shocks. If assets and location are decided jointly or location is decided before assets, the problem becomes intractable. Formally, we need the expectation to be inside the first maximization operator and outside the second maximization operator in equation 4. See appendix A.1 for a proof.

3.2 Worker Aggregation

Now that we have described the worker problem, we turn to characterizing the migration flows and population distribution. Let $g^{w}(a)$ be the worker's asset policy function. We then derive the migration shares (see appendix A.2), the fraction of workers who start period t with assets a in village i and move to village j at the end of the period:

$$m_{ijt}(a) = \frac{\left(\exp(\beta V_{j,t+1}^{w}(g^{w}(a) - \kappa_{ij}))\right)^{1/\nu}}{\sum_{m \in M(i,a')} \left(\exp(\beta V_{m,t+1}^{w}(g^{w}(a) - \kappa_{im}))\right)^{1/\nu}}. \tag{6}$$

At time t, village i has measure $L_{it}^{w}(a)$ of workers with assets a. The distribution of workers across locations and assets evolves according to

$$L_{jt+1}^{w}(a') = \sum_{i \in N} \int_{a: g^{w}(a) - \kappa_{ij} = a'} m_{ijt}(a) L_{it}^{w}(a)\, da \tag{7}$$

where the measure of workers with assets a' in village j at time $t+1$ is the sum over all villages of the workers who start period t with assets a, choose to migrate to village j and arrive with assets a'. The total labor supply in each village is

$$L^w_{jt} = \int_a L^w_{jt}(a)da. \tag{8}$$

3.3 Entrepreneur Problem

Entrepreneurs similarly maximize lifetime utility, discounted at rate β. Unlike workers, however, entrepreneurs permanently reside at their original location[18]. Within a village, entrepreneurs are all born with the same endowment a_0 and the same constant productivity z[19], so per village, we can consider a continuum of identical firms that take factor prices as given. The recursive formulation of the entrepreneur's problem is

$$V^e_i(a,z) = \max_{a' \geq 0}\{u((1+r)a + \pi_i(a,z) - a') + \beta \mathrm{E}[V^e_i(a',z)]\} \tag{9}$$

where $\pi_i(a,z)$ is the maximum profits the entrepreneur in village i can earn given assets a and productivity z.

Entrepreneurs employ production technology

$$f(k,l) = z(k^\alpha l^{1-\alpha})^{1-\gamma}$$

where $1-\gamma$ is the share of output allocated to the factor inputs. The entrepreneurs pay wage w for labor ℓ and rent capital k at rate r.

The amount of capital an entrepreneur can employ is limited by their assets and a collateral constraint $\phi > 1$:

$$k \leq \phi a.$$

[18]In Felkner and Townsend (2011), individuals must return to their original village if they wish to become entrepreneurs. Entrepreneurs are, in other words, location constrained. Their model replicates salient features of business concentration and growth.

[19]We assume the productivity is constant within a village for several reasons. First, Paweenawat and Townsend (2014) find that productivity persistence is close to 1. Second, this is isomorphic to entrepreneurs within a village having uncorrelated productivity shocks. Aggregating to the village level, productivity will be constant. Third, allowing for correlated village level shocks makes the workers' problem intractable since they must now keep track of the distribution of productivities across villages.

The optimal input choice problem is

$$\pi(a,z) = \max_{k,\ell}\{z(k^{\alpha}\ell^{1-\alpha})^{1-\gamma} - w\ell - rk\}$$
$$\text{s.t } k \leq \phi a$$

We derive the optimal input choices in appendix A.3.

3.4 Entrepreneur Aggregation

Entrepreneurs do not migrate, so the total mass entrepreneurs per village, L_i^e, is constant over time. Entrepreneurs, however, can either save or spend assets, so we must keep track of the distribution of entrepreneurial assets. Let $L_{it}^e(a)$ be the measure of entrepreneurs with assets a in village i and time t. The law of motion for entrepreneurial wealth is

$$L_{it+1}^e(a') = \int_{a:a'=g_a^e(i,a)} L_{it}^e(a)da \quad \forall i \tag{10}$$

In each village i, aggregate labor demand for workers is given by $L_i^e\ell_i^*$, the mass of entrepreneurs times the optimal labor demand per entrepreneur.

3.5 Stationary Equilibrium

Define $\{g_a^w(i,a), g_a^e(i,a)\}$ to be the worker's and entrepreneur's policy functions for assets, respectively. Then a stationary equilibrium is a set of wages $\{w(i)\}$, interest rate R, policy functions $\{g_a^w(i,a), g_a^e(i,a)\}$, and distributions of workers and entrepreneurs across villages and assets $L_{it}^w(a), L_{it}^e(a)$ such that (1) Given wages $\{w(i)\}$, workers optimize equation (5); (2) Given wages $\{w(i)\}$, entrepreneurs optimize equation (9); (3) Labor markets clear in each village, $L_{it}^w = L_i^e\ell_{it}, \forall i, t$; (4) The distribution of workers across villages and assets is stationary, $L_{it}^w(a) = L_{it+1}^w(a), \forall i, t$; and (5) The distribution of entrepreneurs across villages and assets is stationary, $L_{it}^e(a) = L_{it+1}^e(a), \forall i, t$.

3.6 Discussion

We make two assumptions about the workers' problems. First, we do not allow for labor adjustment on the intensive margin. Bonhomme et al. (2014) find that wage elasticity for workers in Thailand is low and often insignificant. They find no changes in labor supply in response to wage or income shocks. Including labor choice keeps the results the same while needlessly complicating the model. Second, workers cannot choose to become entrepreneurs.

Although including occupation choice is common in models of village economies (e.g., Beura, Kaboski, and Shin (2017)), there are several reasons we choose not to include it. First, Kaboski and Townsend (2011) find that the village fund intervention had no statistically significant effect on occupation choice. Workers did not become entrepreneurs because of the infusion of credit and vice versa. Second, Banerjee, Breza, Duflo and Kinnan (2015) find considerable benefits in business scale and performance six years after a financial intervention in India for "gung-ho entrepreneurs" who started a business before the financial intervention but not for "reluctant entrepreneurs" without a prior business. Many "reluctant entrepreneurs" switch back to being workers several years post-intervention. The results suggest that heterogeneity in entrepreneurial ability is salient and persistent; the effects are most substantial for entrepreneurs at the intensive rather than extensive margin. Third, as in Moll (2014) and Itshoki and Moll (2018), splitting the entrepreneur and worker problem provides much-needed tractability. We thus consider the worker and entrepreneur problems separately.

On the entrepreneur side, we make three assumptions. First, we assume that entrepreneurs are immobile across space. Since it is costly to move capital and entrepreneurs' migration rates are low to begin with, we abstract away from this issue. Felkner and Townsend (2011) find that limiting an entrepreneur's migration ability provides a good approximation of where businesses locate and which areas develop over time. Second, we assume the production function is decreasing returns to scale. The decreasing returns to scale production function is consistent with estimates from Paweenawat and Townsend (2014). Furthermore, as is the case in Moll (2014) or Itoshoki and Moll (2018), financial constraints are not binding in the long run when the production function is constant returns to scale. Third, we model financial constraints through a reduced form collateral constraint as in Kaboski and Townsend (2012) and Buera, Kaboski, and Shin (2017). One can micro-found the collateral constraint through limited commitment. Karaivanov and Townsend (2014) distinguish between financial constraints and find that limited liability is the binding constraint for most Thai entrepreneurs[20].

3.7 Calibration

We parameterize the model to match key features of Thailand's economy using pre-intervention cross-sectional data from 2001. We calibrate most parameters externally, by primarily draw-

[20]Of course, there is heterogeneity in which constraint binds. Subsequent work by Ru and Townsend (2018) found that the credit regime switched from limited borrowing and lending to costly state verification for the lowest wealth quartile. Furthermore, those with kin working at the village banks are estimated to have the lowest verification cost. We abstract away from these issues.

ing on previous research in Thailand. We calibrate one parameter internally via Simulated Method of Moments. Table 3 reports the estimated values and sources.

The set of parameters in the worker problem is $\{\beta, \nu, R\}$. We set the discount rate of the workers and entrepreneurs to $\beta = 0.9$, which was estimated by Ji and Townsend (2018) for Thailand. We set the migration elasticity $1/\nu$ to 3, following Morten et al (2018)'s estimate of 3 for Indonesia[21]. The workers also take the interest rate as given. In our simulations, we set the interest rate to $R = 1.05$, which is Thailand's national interest rate in 2001 at the start of the Village Fund as documented by the World Bank[22].

The set of parameters in the entrepreneur problem is $\{\beta, R, \gamma, \alpha, \{z_i\}\}$. We set a common β and R for workers and entrepreneurs. Parameters for the production function of Thailand entrepreneurs have been previously estimated by Paweenawat and Townsend (2014) using the Townsend Thai Data. They estimate that the factor share is $\gamma = 0.16$ and the capital share is $\alpha = 0.33$. As mentioned earlier, we assume that productivity z_i is constant within a village but varies across villages. Paweenawat and Townsend (2014) find that productivity across villages within a province is distributed normally with a mean of 3.4 and a standard deviation of 0.1. In each simulation, we randomly draw the productivity for each village from this distribution.

Although the populations of workers in each village are endogenous outcomes of the model, the total population in the economy is determined ex-ante. From the CDD, the mean population in each village is 120. Previous studies using the Townsend Thai Data have determined that the ratio of workers to entrepreneurs is roughly 2 to 1. We thus set the total number of workers and entrepreneurs to be 80 and 40 times the number of villages, respectively. Specifically, $L^w = 2L^e = 80N$, where N is the number of villages[23].

[21] Balboni (2020) reviews the range of estimates for developing countries and find that estimates range from 2 to 4. We can alternatively calibrate $1/\nu$ internally. We estimate that the migration elasticity $\nu = 2.7$, which is slightly lower than Morten et al (2018)'s estimate of 3 for Indonesia, but within the range of other estimates surveyed by Balboni (2020) for developing countries.

[22] Although we can solve for R through a capital market clearing condition, we prefer to set R exogenously. Since we do not observe cities such as Bangkok in the data, we do not include them in our model. Bangkok, in particular, serves as the locus of economic activity in Thailand. At a given interest rate, households in Bangkok are willing to supply any amount of capital to rural villages. This is supported by the work of Paweenawat and Townsend (2014), which finds a convergence of village interest rates in Thailand to a common interest rate of 5%. In practice, this means we do not need to include a capital market clearing condition as capital markets will "clear" at any interest rate.

[23] In the calibrated economy, the relationship $L_i^w = 2L_i^e$ holds for each village i. In counterfactuals, L_i^e is fixed, but L_i^w can vary.

Table 3: Calibration of Model Parameters

Parameter	Description	Value	Source
Panel A. External Calibration			
R	Interest Rate	1.05	World Bank
ϕ	Loan-to-collateral ratio	1.2	Ji and Townsend (2018)
β	Discount Rate	0.95	Ji and Townsend (2018)
γ	Factor Share	0.18	Paweenawat and Townsend (2014)
α	Capital Share	0.3	Paweenawat and Townsend (2014)
$E[Z_i]$	TFP Mean	3.4	Paweenawat and Townsend (2014)
$Var[Z_i]$	TFP Standard Deviation	0.1	Paweenawat and Townsend (2014)
L^w	Total Worker Population	80N	CDD
L^e	Total Entrepreneur Population	40N	Townsend Thai Data
$1/\nu$	Migration Elasticity	3	Morten et al (2020)
Panel B. Internal Calibration			
ξ	Distance Elasticity	0.04	SMM

We are left with one parameter to calibrate internally: the migration cost matrix, κ. To generate κ, we assume that κ is a function of the distances between villages and must first create a matrix of bilateral distances $[d_{ij}]$. We thus split the calibration into two sequential steps. First, we calibrate the location of villages in the model pseudo map to match features of the geographic distribution of villages in Thailand. Second, taking the location of villages as given, we calibrate the migration cost matrix to match baseline distributions of wages and populations in Thailand pre-intervention.

In the first step, we generate a model pseudo map. Modeling all the villages in our sample is computationally infeasible[24]. We reduce the dimensionality of the problem by working with $N = 25$ villages, the mode number of villages within 5km of each other[25]. By reducing the dimensionality of the geography, we let village locations in the model to capture relevant features of the locations of villages in Thailand. One such relevant feature is the distribution of distances to the nearest village. Thai villages are often clustered together, and the distance to the nearest village is one way of encapsulating this phenomenon. We choose several moments of this distribution, including the mean, variance, and skewness, and calculate equivalent moments in the model. Table 4 shows the goodness of fit for pseudo map calibration; the model distribution closely matches the distribution in the data.

[24] Ji and Townsend (2018) consider the geographic problem of expanding spatial bank branches with endogenous dynamic occupation choice in the context of transactions costs on credit and saving decisions. Computational constraints forced a geographic aggregation of villages into markets. Though there can be labor migration, this is limited to a market-level wedge, i.e. workers can stay in the home market or migrate at a cost but, given out-migration, get randomly assigned nationally to clear all markets independent of distance.

[25] Although 25 villages is the most realistic, we are able to capture the relevant spatial features in the data with as few as 15 villages or as many as 75. See Table 6 in the appendix for goodness of fit and robustness checks.

Table 4: Goodness of Fit of Pseudo Map

Distribution of distances to the nearest village	Mean	Variance	Skew
Data	0.12	0.01	2.37
Model	0.07	0.02	2.58

Notes. Goodness of fit of the model pseudo map. The pseudo map is calibrated with 25 villages, where the target moments are the mean, variance, and skewness of the distribution of distances to the nearest village. The distances are normalized so that the largest possible between villages is 1.

In the second step of the calibration, we use Simulated Method of Moments (SMM) to construct the migration cost matrix κ which captures the cost of migrating between any two villages i and j. To do so, we parameterize migration costs as a function of distance, d_{ij}, which was generated in the previous step[26]. Specifically, we let $k_{ij} = \exp(\xi d_{ij})$, as in Alfreht et al (2015)[27]. We target the variance of the wages since, in our model, the migration costs determine the extent to which differences in productivity across villages generate differences in wages. Larger migration costs limit migration, increasing wage differentials across villages. Our estimate of ξ, the change in κ for a unit change in distance (km), is 0.04, which is close to Alfreht et al (2015)'s estimate of 0.06. Although our settings ostensibly differ, a common feature is local migration. This suggests that 0.04 is a reasonable estimate of the elasticity of migration costs with respect to distance. It is also informative to consider the size of the migration costs directly. Given the estimate of ξ, migration costs are on average 4 times the wage. These costs may seem large but are consistent with previous estimates of migration costs[28].

3.8 The Village Fund

We model the 'Million Baht Village Fund' program as a permanent relaxation of entrepreneurs' leverage constraints from ϕ_i to ϕ_i'. We let $(\phi_i' - \phi_i)a_i^e = 1,000,000$ Baht$/L_i^e, \forall i$, such that the initial change in the amount borrowed by an entrepreneur in each village (left-hand side) is equal to the amount available to an entrepreneur in each village (right-hand side)[29]. The expression implies that the total amount borrowed is the same per village; the change in the leverage constraint induces borrowing of 1 million baht. We want entrepreneurs to use the

[26] When estimating the gravity equation it is often common to include covariates other than distance such as language or ethnic barriers. These are not an issue here since we are modeling 5 km spillovers. Locally, non-distance barriers such as language and ethnicity are less of a concern.

[27] Although this functional form would allow one to calibrate the ξ by estimating a semi-parametric gravity equation as in Alfreht et al (2015), we do not have data on bilateral migration flows and thus calibrate ξ through SMM.

[28] Kennan and Walker (2011) estimate migration costs in the US to be \$300,000, several times the average wage. Similarly, Diamond (2016) estimates migration costs in San Francisco for low-income residents to be \$50,000, which is again several times the wage income of the moving agents. Several theories posit why estimated migration costs are so large, including various forms of miss-specification.

[29] When entrepreneurs are constrained they borrow up to the leverage constraint which is given by $\phi_i a_i^e$.

entire amount available to them, consistent with what is observed in the data. Furthermore, entrepreneurs in small villages have more credit access than those in larger villages, so the change in credit per capita decreases in population size.

We model the village fund as a one-time, permanent change in entrepreneur leverage constraints for two reasons. First, banks in each village would issue new loans upon being repaid by borrowers, thus permanently increasing the amount of credit available. This is supported empirically by the findings of Kaboski and Townsend (2011), who document that the village fund intervention had persistent impacts on credit availability: total credit available to villagers increased in the short- and long-term. Second, Kaboski and Townsend (2011) find that most villages lent out the entire amount available within a year of the program's start. We think of the quick disbursement of funds as a one-time shock to leverage constraints.

We simulate the 'Million Baht Village Fund' program and estimate the effects of credit per capita on wages and populations. Comparison of the coefficients in the model vs data is an important test of external validity. The coefficients on the regressions of credit per capita on wages and populations are untargeted moments in the calibration. The calibration targets pre-intervention cross-sectional moments, whereas the regression coefficients capture the difference between pre- and post-intervention. If the model is miss-specified, parameters calibrated to cross-sectional data would not allow us to match differences across time.

We report the results in Table 5. Columns (1) and (2) show the coefficient on wages, and columns (3) and (5) show the coefficient on population. The coefficients on the direct and spillover effects of credit on wages in the model are qualitatively consistent with the coefficients in the data along four dimensions. First, comparing to the effect on wages in table 9 and 11, credit intensity positively affects wages: a larger infusion of credit per capita in the target village increases the village wage. Second, neighboring village credit intensity has a positive spillover effect on wages: a larger infusion of credit per capita in neighboring villages increases the wages of the target village. Third, as in the data, the spillover effect is the model greater than the direct effect. Fourth, compared to the effect on population in table 13, a larger infusion of credit per capita in the target village increases the population.

The coefficients in the model and the data are also quantitatively similar. Our model and data estimates are within an order of magnitude from each other. We should not expect the coefficients to match exactly. Given the abstractions from within and across-village mechanisms, we cannot precisely match the coefficients. Nor do we intend to. Yet despite these abstractions, our model performs remarkably well: a 10,000 baht increase in credit per capita increases wages by 0.8% in the data and 1% in the model. A 10,000 baht increase in credit per capita has a spillover effect of increasing wages by 2% in the data and 6% in the model. And finally, a 10,000 baht increase in credit per capita increases populations by 4% in the data and 6% in the model. The results are robust to various specifications, including using levels instead of logs.

Table 5: Village Fund Simulation Regressions

VARIABLES	(1) Wage	(2) Log Wage	(3) Pop	(4) Log Pop	(5) Capital	(6) Log Capital	(7) Profit	(8) Log Profit
Credit	0.360***	0.00263***	0.442	0.0240***	3.092***	0.0294***	9.009***	0.0109***
	(0.0520)	(0.000434)	(0.333)	(0.00263)	(0.554)	(0.00477)	(2.884)	(0.00287)
NeighborhoodCredit	7.314***	0.0662***	-6.735	-0.116	-82.23***	-0.377***	-396.0***	-0.300***
	(1.972)	(0.0178)	(10.48)	(0.0873)	(18.09)	(0.105)	(91.97)	(0.0803)
Constant	97.91***	4.576***	86.27***	3.867***	298.5***	5.245***	1,737***	7.252***
	(3.314)	(0.0286)	(19.06)	(0.138)	(30.00)	(0.178)	(150.9)	(0.133)
Observations	50	50	50	50	50	50	50	50
R^2	0.664	0.673	0.495	0.825	0.697	0.555	0.619	0.533
Village FE	YES	YES	YES	YES	YES	YES	YES	YES

Notes. This table reports the results of equation 2 on wages, population, capital, and profits using the model simulated Thai Village Fund. Reported values are for the coefficient on credit and neighborhood credit and standard errors are in parentheses. In columns (1) and (2), wages are the daily wage of workers (in Baht). In columns (3) and (4), population is measured as the number of workers in each village. In columns (5) - (8), capital and profits are measured as yearly aggregates for each village (in Baht). *** p<0.01, ** p<0.05, * p<0.1

3.9 Welfare and Distributional Effects

The Village Fund deferentially affects agent welfare by occupation, wealth, and location. Figure 4 breaks down the aggregate welfare gains by occupation. Aggregate welfare increases for workers but decreases for entrepreneurs. Although the Village Fund's direct effects benefit both agents, spatial spillovers generate a welfare trade-off between workers and entrepreneurs. This can be observed in Table 5. The first row of Table 5 shows the direct effects of the Village Fund. Relaxing leverage constraints increases firm usage of capital and labor and ultimately increases profit and wages. The welfare of both workers and entrepreneurs increases as a result. The second row of Table 5 shows the spillover effects of the Village Fund. As seen in column (4), credit spillovers reduce the population of neighboring villages by encouraging out-migration. To clear labor markets, wages of neighboring villages must also increase. Thus the spillovers increase worker welfare in neighboring villages. However, from the perspective of firms, out-migration increases the price of labor, decreasing their demand for workers. This reduces the demand for capital, captured by the negative coefficient in column (6). And finally, it lowers profits, as shown in columns (8). This lowers entrepreneur welfare[30].

[30]Not all village linkages can generate the welfare trade-off between occupations. Consider, for instance, an environment with no migration but positive inter-village capital flows. Relaxing borrowing constraints increases capital flows, reducing leverage constraints in neighboring villages. This generates positive spillover effects on entrepreneurs, increasing the welfare of entrepreneurs and workers hand-in-hand. Now consider an environment with trade flows but no migration. Increased demand for non-tradable goods would increase profits and wages in neighboring villages. Although wages increase, the effect of trade is ambiguous and depends on the composition of tradable and non-tradable goods in the utility function. Relative to capital or trade flows, migration generates a trade-off between workers and entrepreneurs because aggregate labor supply is inelastic and independent of firm leverage constraints. A more thoughtful treatment of the roles and interactions of these mechanisms is warranted, although outside the scope of this paper.

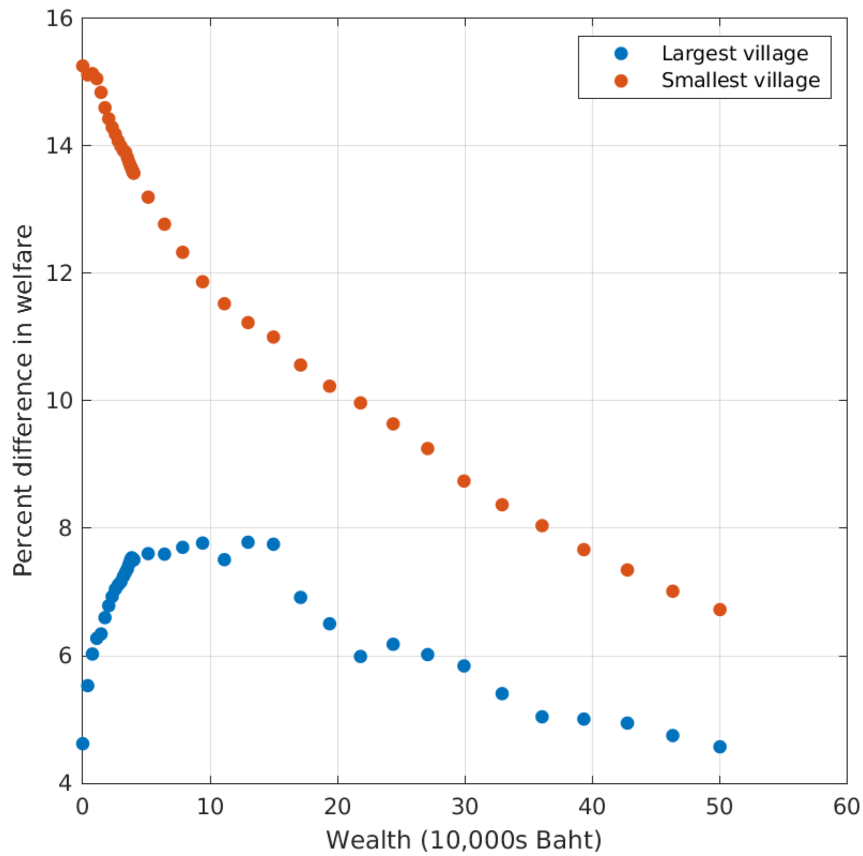
The Village Fund also had distributional effects for workers by wealth and the village of residence. Figure 3 shows the percent change in consumption-equivalent welfare due to the Village Fund by wealth for the largest and smallest village. The values should be interpreted as the difference in average welfare for an individual with assets a in each steady state[31]. First, as we see from figure 3, there are distributional effects for workers by village size. For any given level of assets, workers in the smallest village have a bigger increase in welfare than workers in the largest village. Although the relationship is not strictly monotonic due the rich spatial configuration of villages, welfare changes are generally largest for smaller villages and smallest for the largest villages. This is because the Village Fund program provided credit inversely proportional to the population of each village. Smaller villages received more funding per person which relaxed leverage constraints and increased wages more than in larger villages. One might suspect the opposite relationship from the magnitudes of the positive direct effect and positive spillover effect reported in table 5. However, table 5 only captures the effect of funding, not how the funding is distributed across villages. Since large villages received very little credit per capita, their leverage constraints remained virtually unchanged, so all the welfare gains are through the spillovers. On the other hand, small villages received a lot of credit per capita, so most of the welfare gains are through the within-village effects.

There are also distributional effects for workers by wealth. As shown in figure 3, the benefits of increased credit infusion are monotonically decreasing in wealth for the smallest village and non-monotonic in wealth for the largest village. Consider first what happens in the smallest village. The greatest percent change in welfare in the small is for the poorest, who are borrowing-constrained. As wealth increases, individuals are less credit constrained and therefore experience a smaller increase in welfare. This is because, within a village, the wage increase is the same for everyone, and higher-wealth individuals start at a higher welfare baseline. In the largest village, however, the largest increase in welfare is in the middle of the credit distribution. This is due to the relaxation of a second pecuniary constraint, migration costs. Because the migration cost is pecuniary, households lacking funds cannot migrate to the villages with the highest wages. While they still benefit from the increased wages caused by the credit infusion and the out-migration from their village, these benefits are less than they could have been had the workers been able to move directly. The small wage increase in the largest village is sufficient to relax this constraint for the middle of the income distribution, such that those in the middle of the wealth distribution now find it beneficial to migrate and can take advantage of the wage differences across villages. This increases

[31] We are not computing transition paths, so one should not interpret this graph as the change in welfare for an individual who starts with assets a in the initial steady state.

their change in welfare relative to those who cannot migrate, the poorest workers who are essentially a captured population. At the top of the wealth distribution, the percent change in welfare decreases again because the wealthiest were already neither migration nor credit constrained.

Figure 3: Distribution of percent change in welfare by wealth



Notes. Figure shows the effect of the Village Fund on welfare by wealth for the largest and smallest villages. Welfare is measured as consumption equivalent. Wealth is measured in 10000 Baht.

3.10 Robustness and Model Mechanics

The results are robust to different parameter values. Varying the migration elasticity ν does not significantly change either the baseline equilibrium or the direction and magnitude of the direct and spillover effects due to the Village Fund program. The results are also robust to different productivity draws and variation in the value of the distance elasticity ξ. We report the robustness results in appendix A.7.

3.11 Counterfactuals

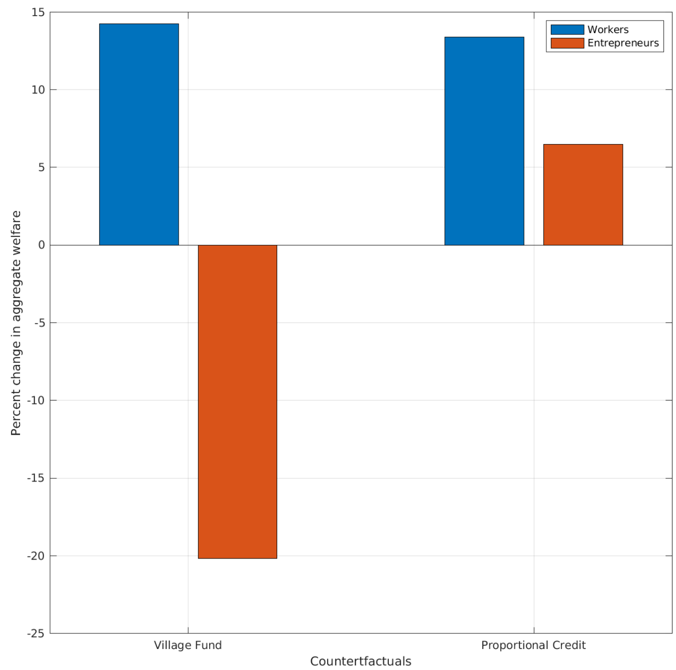
Is allocating credit per capita inversely proportional to village size an effective funding allocation? We test whether an alternative allocation of funds across villages would yield large welfare gains[32]. In the 'Village Fund', credit per village was fixed at 1,000,000 Baht, implying that credit per capita was inversely proportional to village size. We simulate an additional financial intervention where credit per capita is independent of village size, implying that credit per village is allocated proportionally to the population. Formally, we let $(\phi_i' - \phi_i)a_i^e = \bar{c}L_i^e$ for some constant $\bar{c}$ which we derive in appendix A.6. We hold the total amount of funds disbursed constant across all simulations.

Figure 4 presents the aggregate percentage consumption-equivalent welfare gains from the counterfactual simulations relative to the baseline economy. Providing credit per capita inversely proportional to village size (the Village Fund) increased aggregate worker welfare by 14% and decreased aggregate entrepreneur welfare by 20%, while providing credit per capita equally across villages increased aggregate worker welfare by 13% and increased aggregate entrepreneur welfare by 5%. The interaction between the direct and spillover effects is key to understanding these results. In the Village Fund, the smallest villages receive the most credit per capita, so the positive direct effects dominate the negative spillovers resulting in an increase in wages and capital deepening. But this comes at the expense of larger villages, who receive very little credit per capita, and therefore have very small direct effects but experience large negative spillovers from the smaller villages. This leads to an increase in wages but a reduction in capital deepening. On the other hand, when credit is allocated equally per capita (i.e. proportional to village size), the direct effects are spread out more evenly. As a result, they dominate the spillover effects for most villages. This increases welfare for both workers and entrepreneurs.

The results suggest that the key to an effective credit allocation is balancing the tension between financial deepening and spatial misallocation. In a closed economy, financial deepening is beneficial since it reduces financial frictions. However, in our open economy setting with migration between villages, financial deepening in one village can result in a financial decline in another. This is exactly the case with the Village Fund. Financial deepening in smaller villages reduced capital and labor demand in larger villages, generating greater spatial misallocation of credit. Although the overall effects of the Village Fund were positive, the counterfactuals suggest that alternative credit allocations better balance the direct and

[32] We would ideally like to calculate an optimal spatial credit infusion policy to maximize welfare. Optimal spatial policies have been computed in previous works, such as Fajgelbaum and Schaal (2017), Fajgelbaum and Gaubert (2018), and Allen, Arkolakis, and Li (2015). These models, however, are static. As of yet, not math exists for deriving optimal spatial policies in dynamic models.

Figure 4: Welfare gains of counterfactual simulations



spillover effects.

4 Conclusion

We study the design of a scaled-up financial intervention and the role of migration in mediating the incidence of financial policy. Interpreting the natural experiment through the lens of the model, we find large distributional effects by village, wealth, and occupation. In particular, pecuniary migration constraints prevent low-income and low-wealth individuals from taking advantage of increasing wage differentials with other villages. Furthermore, migration generates a trade-off between workers and entrepreneurs, raising wages to the benefit of workers but at a cost to entrepreneurs.

Our paper highlights the importance of accounting for the interaction of migration and financial frictions when considering the impact of scaled-up policy. In the case of the Village Fund, migration generated equilibrium spillovers that were over 10 times larger than the within-village equilibrium effects. Studying the effect of the intervention solely within the context of a single village would miss how the rich spatial structure of villages interacts with the intervention. Policies must account for how village linkages could re-allocate welfare gains between different locations and agent types. More work remains to be done understanding the interaction between inter-village linkages and financial frictions in equilibrium.

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A Model Appendix

A.1 Derivation of Value Function

The value function of a worker with assets a in village i at time t is

$$V_{i,t}^{w}(a) = \max_{a' \geq -\bar{a}} \{u((1+r)a + w_{i,t} - a') + \mathrm{E}[\max_{j \in M}\{\beta V_{j,t+1}^{w}(a' - \kappa_{ij}) + \epsilon_{j,t}\}]\}$$

Assume that the idiosyncratic location shock ϵ is i.i.d and drawn from a Gumbel distribution with parameters $(-\bar{\gamma}\nu, \nu)$, where $\bar{\gamma} \equiv \int_{-\infty}^{\infty} x \exp(-x - \exp(-x))\, dx$ is Euler's constant. The cumulative distribution and density functions of this distribution are

$$F(\epsilon) = \exp(-\exp(-\frac{\epsilon}{\nu} - \bar{\gamma}))$$
$$f(\epsilon) = \frac{1}{\nu}\exp(-\frac{\epsilon}{\nu} - \bar{\gamma} - \exp(-\frac{\epsilon}{\nu} - \bar{\gamma}))$$

Let $\bar{\epsilon}_{jm,t} = \beta(V_{j,t+1}^{w}(a' - k_{ij}) - V_{m,t+1}^{w}(a' - k_{im}))$. Then the second term in the maximization can be rewritten as

$$\Phi_t^j = \mathrm{E}[\max_{j \in M}\{\beta V_{j,t+1}^{w}(a' - \kappa_{ij}) + \epsilon_{j,t}\}] =$$
$$= \sum_{j \in M} \int (\beta V_{j,t+1}^{w}(a' - \kappa_{ij}) + \epsilon_{i,t}) f(\epsilon_{i,t}) \Pi_{m \neq j} F(\bar{\epsilon}_{jm,t} + \epsilon_{i,t})\, d\epsilon_{j,t}$$

Substituting in $F(\epsilon)$ and $f(\epsilon)$ we have

$$\Phi_t^j = \sum_{j \in M} \int (\beta V_{j,t+1}^{w}(a' - \kappa_{ij}) + \epsilon_{j,t})(\frac{1}{\nu})\exp(-\frac{\epsilon_{j,t}}{\nu} - \bar{\gamma}))\exp(-\sum_{m \in M}\exp(-\frac{\epsilon_{jm,t}}{\nu} - \frac{\epsilon_{j,t}}{\nu} - \bar{\gamma}))\, d\epsilon_{j,t}$$

Define $\lambda_t = \log \sum_{m \in M} \exp(-\frac{\bar{\epsilon}_{jm,t}}{\nu})$, $x_t = \frac{\epsilon_{j,t}}{\nu} + \gamma$, and $y_t = x_t - \lambda_t$, and apply a change of variables. Then

$$\Phi_t^j = \nu \log(\sum_{j \in M}(\exp(\beta V_{j,t+1}^{w}(a' - \kappa_{ij})))^{1/\nu})\}$$

And

$$V_{i,t}^{w}(a) = \max_{a' \geq -\bar{a}} \{u((1+r)a + w_{i,t} - a') + \nu \log(\sum_{j \in M}(\exp(\beta V_{j,t+1}^{w}(a' - \kappa_{ij})))^{1/\nu})\}$$

A.2 Derivation of Migration Shares

The fractions of migrants from location i to location j given initial assets a at the end of period t is:

$$\begin{aligned} m_{ijt}(a) &= \Pr[\beta V^w_{j,t+1}(g^w(a) - k_{ij}) + \epsilon_{j,t} \geq \beta V^w_{m,t+1}(g^w(a) - k_{im}) + \epsilon_{m,t}, m = 1, ..., M] \\ &= \int f(\epsilon_{j,t}) \Pi_{m \neq j} F(\beta(V^w_{j,t+1}(g^w(a) - k_{ij}) - V^w_{m,t+1}(g^w(a) - k_{im})) + \epsilon_{j,t})\, d\epsilon_{j,t} \end{aligned}$$

As earlier, let $\bar{\epsilon}_{jm,t} = \beta(V^w_{j,t+1}(g^w(a) - k_{ij}) - V^w_{m,t+1}(g^w(a) - k_{im}))$. Substitute in $\bar{\epsilon}_{jm,t}$ and the cumulative distribution and density functions of the Gumbel distribution:

$$\begin{aligned} m_{ijt}(a) &= \int (\frac{1}{\nu}) \exp(-\frac{\epsilon_{j,t}}{\nu} - \gamma - \exp(-\frac{\epsilon_{j,t}}{\nu})) \Pi_{m \neq j} \exp(-\exp(-\frac{\bar{\epsilon}_{jm,t}}{\nu} - \frac{\epsilon_{j,t}}{\nu} - \gamma))\, d\epsilon_{j,t} \\ &= \int (\frac{1}{\nu}) \exp(-\frac{\epsilon_{j,t}}{\nu} - \gamma) \exp(-\sum_{m \in M} \exp(-\frac{\bar{\epsilon}_{jm,t}}{\nu} - \frac{\epsilon_{j,t}}{\nu} - \gamma))\, d\epsilon_{j,t} \end{aligned}$$

Allowing for a change of variables where λ_t, x_t, and y_t are defined as earlier, we have

$$\begin{aligned} m_{ijt}(a) &= \int (\frac{1}{\nu}) \exp(-x_t) \exp(-\exp(\lambda_t) \exp(-x_t)) \nu \, dx_t \\ &= \int \exp(-y_t - \lambda_t) \exp(-\exp(\lambda_t) \exp(-y_t - \lambda_t))\, dy_t \\ &= \exp(-\lambda_t) \int \exp(-y_t - \exp(y_t))\, dy_t \\ &= \exp(-\lambda_t) \\ &= \frac{(\exp(\beta V^w_{j,t+1}(g^w(a) - \kappa_{ij})))^{1/\nu}}{\sum_{m \in M} (\exp(\beta V^w_{m,t+1}(g^w(a) - \kappa_{im})))^{1/\nu}} \end{aligned}$$

A.3 Derivation of Optimal Input Choices

Entrepreneurs employ production technology

$$f(k, l) = z(k^\alpha l^{1-\alpha})^{1-\gamma}$$

where $\alpha, \gamma < 1$, as well as pay wage w for labor l and rent capital k at rate r. The amount of capital an entrepreneur can employ is limited by their assets and a collateral constraint

$\phi > 1$. The optimal input choice problem is therefore

$$\pi(a) = \max_{k,l}\{z(k^\alpha l^{1-\alpha})^{1-\gamma} - wl - rk\}$$
$$\text{s.t } k \leq \phi a$$

Taking the first order conditions we have that

$$z\alpha(1-\gamma)k^{\alpha(1-\gamma)-1}l^{(1-\alpha)(1-\gamma)} = r + \lambda$$
$$z(1-\alpha)(1-\gamma)k^{\alpha(1-\gamma)}l^{(1-\alpha)(1-\gamma)-1} = w$$

where λ is the shadow price of capital. If the leverage constraint is not binding, then the first order conditions are

$$z\alpha(1-\gamma)k^{\alpha(1-\gamma)-1}l^{(1-\alpha)(1-\gamma)} = r$$
$$z(1-\alpha)(1-\gamma)k^{\alpha(1-\gamma)}l^{(1-\alpha)(1-\gamma)-1} = w$$

Dividing the two equations we have

$$\frac{w}{r} = \frac{1-\alpha}{\alpha}\frac{k}{l}$$
$$l = \frac{r}{w}\frac{1-\alpha}{\alpha}k$$

which we substitute into the first order condition with respect to capital

$$\begin{aligned} r &= z\alpha(1-\gamma)k^{\alpha(1-\gamma)-1}\left(\frac{r}{w}\frac{1-\alpha}{\alpha}k\right)^{(1-\alpha)(1-\gamma)} \\ &= z\alpha(1-\gamma)k^{(1-\gamma)-1}\left(\frac{r}{w}\frac{1-\alpha}{\alpha}\right)^{(1-\alpha)(1-\gamma)} \\ k^* &= \left[z\left(\frac{1-\alpha}{\alpha}\frac{r}{w}\right)^{(1-\alpha)(1-\gamma)}\frac{\alpha(1-\gamma)}{r}\right]^{\frac{1}{1-(1-\gamma)}} \end{aligned}$$

We can also re-arrange the first order condition with respect to labor

$$l^* = \frac{r}{w}\frac{1-\alpha}{\alpha}k^*$$

If the leverage constraint is binding, the optimal capital input choice is

$$k^* = \phi a$$

Then the optimal labor input is given by

$$\pi(a) = \max_{l}\{z((\phi a)^{\alpha} l^{1-\alpha})^{1-\gamma} - wl - r(\phi a)\}$$

and the first order conditions are

$$\begin{aligned} w &= z(1-\alpha)(1-\gamma)(\phi a)^{\alpha(1-\gamma)} l^{(1-\alpha)(1-\gamma)-1} \\ l^* &= \left[\frac{z}{w}(1-\alpha)(1-\gamma)(\phi a)^{\alpha(1-\gamma)}\right]^{\frac{1}{1-(1-\alpha)(1-\gamma)}} \end{aligned}$$

We thus have that optimal input choices are

$$\begin{aligned} k^* &= \min\left\{\left[z\left(\frac{1-\alpha}{\alpha}\frac{r}{w}\right)^{(1-\alpha)(1-\gamma)}\frac{\alpha(1-\gamma)}{r}\right]^{\frac{1}{1-(1-\gamma)}}, \phi a\right\} \\ l^* &= \left[\frac{z}{w}(1-\alpha)(1-\gamma)(k^*)^{\alpha(1-\gamma)}\right]^{\frac{1}{1-(1-\alpha)(1-\gamma)}} \end{aligned}$$

A.4 Equilibrium Computation

Although the worker problem in our model resembles the models of Caliendo et al (2018) and Balboni (2018), our computational methods most closely resemble that of Lyon and Waugh (2018). The procedure is as follows:

(1) Guess the wage function $w(i)$ (i.e guess wage w_i for every village i).

(2) For a worker in every village and asset level, solve the worker problem using value function iteration. The value function iteration is standard other than one step: although the asset grid is discretized and so is the asset policy function, $g(i,a) - k_{ij}$ is a continuous function since k_{ij} is continuous. We must therefore "snap" $g(i,a) - k_{ij}$ to the nearest point on the asset grid.

(3) Construct stationary distribution for workers using the migration shares and worker asset policy function. This involves creating a transition matrix from the policy functions and iterating on it until a stationary distribution is reached.

(4) For an entrepreneur in every village and asset level, solve the entrepreneur problem using value function iteration.

(3) Construct stationary distribution for entrepreneurs using the entrepreneur asset policy function.

(4) Use the stationary distributions for workers and entrepreneurs to construct labor supply and demand in each village. Check if the labor markets clear in each village.

(5) If the error in the labor market clearing condition is larger than some threshold, update the wage function and repeat the previous steps until the wage function converges to a stationary equilibrium. The model can be depicted as a system of nonlinear equations taking where the input is a wage vector and the output is an error vector in labor market clearing. Standard optimizing functions in Matlab are unable to solve this system, so we turn to proprietary solvers (NAG toolbox c05qc solver), that uses a modification of the Powell hybrid method.

A.5 Calibration

To generate a pseudo map, we assign locations to villages in the model through the following procedure. We assume that villages are located on the circumference of a circle as in figure 5. Then the only parameters that govern distances between villages on the circle is the angle, which we draw randomly from a distribution, and the radius, R. In our calibration, we use the $Beta(a, b)$ distribution. The beta distribution is convenient because it has a domain on $[0, 1]$. Once we draw $\theta \sim Beta(a, b)$, we multiply $\theta \times 360$, which gives us the angle of the village. Thus the parameters that we calibrate are $\{a, b, R\}$. We calibrate the radius and the parameters of the angle distribution using the method of simulated moments to minimize the difference between the data and model moments. The calibration procedure works for different numbers of villages, as shown in table 6.

Table 6: Distribution of Distances to Nearest Village

Moments	Data	Number of Villages in Model			
		15	25	50	75
Mean	0.12	0.07	0.07	0.10	0.10
Variance	0.01	0.02	0.02	0.02	0.03
Skew	2.37	2.09	2.58	3.09	3.78

Once the pseudo map is generated, we calibrate the migration costs as a function of distance. Following Lyon and Waugh (2018), we solve for the parameter and equilibrium vector in a single step. We repeat the computation approach in A.4, but with restrictions on matching moments. This significantly reduced the computational cost normally associated

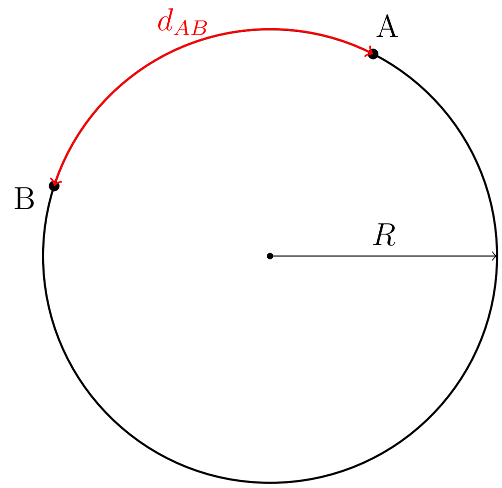


Figure 5: Village Locations in the Model

with first guessing a parameter vector, then solving for the equilibrium given that vector, and then updating the parameter guess.

A.6 Counterfactuals

We now show how to keep the total amount of funding constant across counterfactual simulations. In the Village Fund, we relax credit constraints according to the following formula:

$$\Delta\phi_i a_i^e = \frac{1,000,000 \text{ Baht}}{L_i^w}$$

so that the total amount of credit provided to villages is

$$\sum_{i=1}^{N} \Delta\phi_i a_i^e = \sum_{i=1}^{N} \frac{1,000,000}{L_i^w}$$

When credit is allocated proportional to village size, i.e equally per capita ($\Delta\phi_i a_i^e = \bar{c}L_i^w$), we have

$$\sum_{i=1}^{N} \frac{1,000,000}{L_i^e} = \sum_{i=1}^{N} \Delta\phi_i a_i^e = \sum_{i=1}^{N} \bar{c}L_i^e = \bar{c}\sum_{i=1}^{N} L_i^e = \bar{c}40N$$
$$\bar{c} = \frac{1}{40N}\sum_{i=1}^{N} \frac{1,000,000}{L_i^e}$$

A.7 Model Robustness

We simulate the Village Funds for different parameter values. Key among these is the migration elasticity $1/\nu$ which in the baseline is set to 3 but estimates range from 2 to 4. Simulating the Village Fund, we find that both qualitatively and quantitatively the results are consistent across the range of estimated migration elasticities. The results are reported in table 7. Of note is that the change in the coefficients in non-linear in $1/\nu$, but this may be due to the interaction between wealth and migration. Different migration elasticities will generate different baseline distributions of wealth, which will the generate different responses to the intervention. Overall, the results are remarkably consistent.

Table 7: Village Fund Simulation Regressions

	$1/\nu = 4$		$1/\nu = 3$		$1/\nu = 2$	
	Wage	Log Wage	Wage	Log Wage	Wage	Log Wage
Credit	4.695***	0.0358***	1.630***	0.0115***	2.211***	0.0163***
	(0.619)	(0.00555)	(0.114)	(0.00105)	(0.234)	(0.00173)
Neighbor Credit	8.954***	0.0895***	4.033***	0.0441***	7.320***	0.0749***
	(0.866)	(0.00747)	(0.874)	(0.00891)	(1.288)	(0.0120)
Constant	95.45***	4.555***	94.00***	4.537***	93.91***	4.538***
	(1.542)	(0.0132)	(1.391)	(0.0138)	(1.504)	(0.0138)
Observations	50	50	50	50	50	50
R^2	0.894	0.899	0.930	0.910	0.904	0.904
Village FE	YES	YES	YES	YES	YES	YES

Notes. This table reports the results of equation 2 on wages for different values of ν. Reported values are for the coefficient on credit and neighborhood credit and standard errors are in parentheses. Wages are the daily wage of workers (in Baht). *** p<0.01, ** p<0.05, * p<0.1

We repeat the same exercise for different parametrizations of κ. As mentioned in the main text, we vary the relationship between the migration cost κ_{ij} and the distance d_{ij}. We consider three cases: (1) $\kappa_{ij} = \bar{\kappa}$, (2) $\kappa_{ij} = \exp(\alpha d_{ij})$, and (3) $\kappa_{ij} = \log(\gamma d_{ij})$. Case (2) is the parametrization used in the main text, and is consistent with models of trade and migration featuring gravity. Table 8 reports the results for these simulations. Case (2), $\kappa_{ij} = \exp(\alpha d_{ij})$, is both qualitatively and quantitatively closest with the data estimated regressions. We explain the logic in the text.

Table 8: Village Fund Simulation Regressions

	$\kappa = \bar{\kappa}$		$\kappa = \exp \alpha\kappa$		$\kappa = \log \gamma\kappa$	
	Wage	Log Wage	Wage	Log Wage	Wage	Log Wage
Credit	-1.509**	-0.0171**	2.211***	0.0163***	-0	-0*
	(0.599)	(0.00676)	(0.234)	(0.00173)	(0)	(0)
Neighbor Credit	0.464	0.00525	7.320***	0.0749***	38.81***	0.282***
	(0.437)	(0.00493)	(1.288)	(0.0120)	(6.769)	(0.0358)
Constant	90.54***	4.506***	93.91***	4.538***	103.6***	4.596***
	(0.206)	(0.00231)	(1.504)	(0.0138)	(9.608)	(0.0523)
Observations	50	50	50	50	50	50
R^2	0.806	0.805	0.904	0.904	0.643	0.724
Village FE	YES	YES	YES	YES	YES	YES

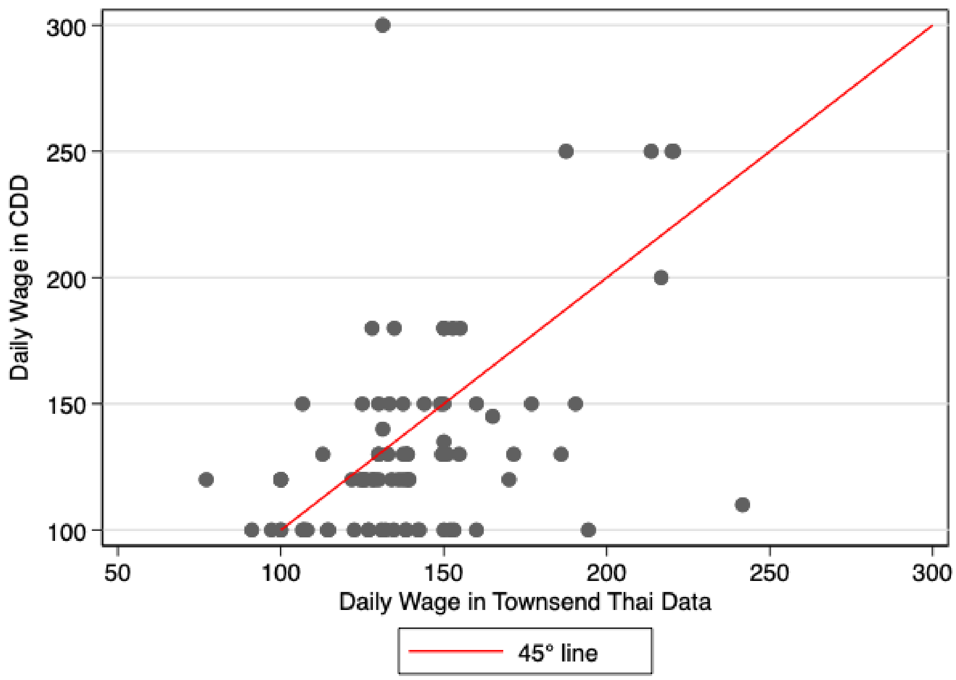
Notes. This table reports the results of equation 2 on wages for different parametrizations of κ. Reported values are for the coefficient on credit and neighborhood credit and standard errors are in parentheses. Wages are the daily wage of workers (in Baht). *** p<0.01, ** p<0.05, * p<0.1

B Data Appendix

B.1 Comparison of CDD and Townsend Thai Data

The CDD reports a single bi-annual value for the daily wage and population. There is, of course, variation in village wages across individuals, occupations, and time. The number of household per village similarly may not take into account time variation due to both temporary and permanent migration, both of which are prevalent in the Thailand (Townsend Thai Project Document 2016). To better understand the wage measure in the CDD, we compare it to non-farming wages collected in the Townsend Thai Data in 2001. As is evident from Figure 6, there is a strong positive correlation between the CDD wages and the wages in the Townsend Thai Data, suggesting measurement error should not be a big concern. There are, of course, differences as well: comparison to the 45°line suggests that the wages in the CDD are slightly lower relative to the wages in the Townsend Thai Data. Differences in measurement can explain this discrepancy. The CDD does not delineate between farming and non-farming wages, whereas the Townsend Thai panel does. Non-farming wages are higher than farming wages, which could be why the CDD reports lower wages. Overall, wages in the CDD are in same ballpark as wages in the Townsend Thai Data and have a strong positive correlation.

Figure 6: Wages in the CDD and Townsend Thai Data



B.2 Fact Robustness

We check our key identification assumption of parallel trends in wages by village size. To test this assumption, we run an event study:

$$y_{it} = \sum_{t=1986}^{2009} \beta_t \text{Credit}_i * \phi_t + \phi_i + \epsilon_{it} \tag{11}$$

where Credit_i is interacted with the time effect. The results are presented in Table 10 and Figure 7. β_t is negative and statistically insignificant for $1986 \leq t \leq 1999$ and positive and statistically significant for $2003 \leq t \leq 2009$. The effects of β_t are measured relative to 2001.

This empirical specification serves to check our main identification assumption of parallel trends. As mentioned earlier, the key identification concern is that different-sized villages have different trends in wages. If smaller villages were to have faster wage growth than larger villages pre-program, then any estimated effects post-program could be due to wage trends rather than per capita credit infusion. Parallel trends would be satisfied if β_t, the coefficient for $\text{Credit}_i * \phi_t$, is not statistically significant for $t \leq 2001$. This is the case in figure 7, where pre-2001 β_t is not statistically different from zero but increases sharply post-2001 to 1%, which it maintains for the duration of our sample. The result is robust to additional specifications, such as controlling for different geographic fixed effects and levels of government, as seen in Table 10. In the few cases when β_t for $t \leq 2002$ is statistically significant, the coefficients are negative, suggesting that larger villages have faster wage growth than smaller villages pre-intervention. This trend is reversed post-treatment, implying that our estimates of β_t are understating the effect of the program.

Table 9: Direct Effect on Wages

VARIABLES	(1) Wage	(2) Wage	(3) Wage	(4) Log Wage	(5) Log Wage	(6) Log Wage
$\text{Credit}_i * \text{Post}$	1.495***	1.508***	1.195***	0.00997***	0.0114***	0.00996***
	(0.221)	(0.202)	(0.176)	(0.00197)	(0.00140)	(0.00121)
Constant	38.70***			3.587***		
	(0.187)			(0.00280)		
Observations	432,783	432,783	432,783	432,783	432,783	432,783
R^2	0.790	0.831	0.851	0.861	0.894	0.906
Number of Villages	39,628			39,628		
Year FE	YES	NO	NO	YES	NO	NO
Village FE	YES	YES	YES	YES	YES	YES
Prov-yr FE	NO	YES	NO	NO	YES	NO
Amphoe-yr FE	NO	NO	YES	NO	NO	YES
Drop Outliers	YES	YES	YES	YES	YES	YES

This table reports the results of equation 1 on wages. Standard errors clustered at tambon-level throughout.
*** p<0.01, ** p<0.05, * p<0.1

Figure 7: Event Study of Credit on Wages with Prov-yr FE

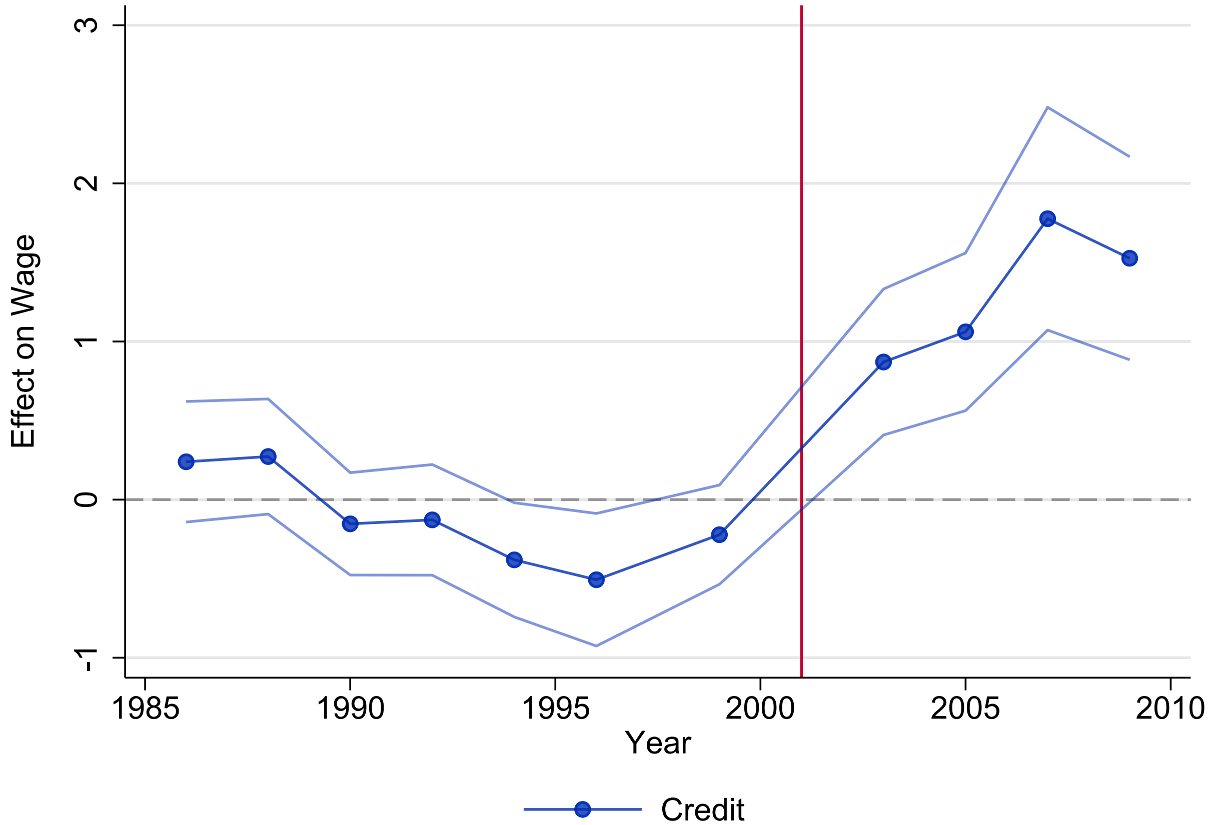


Table 10: Wage Dynamics

VARIABLES	(1) Wage	(2) Wage	(3) Wage	(4) Log Wage	(5) Log Wage	(6) Log Wage
$Credit_i * 1986$	-0.652***	0.264	0.400**	0.000684	0.00317	0.00276
	(0.244)	(0.216)	(0.191)	(0.00312)	(0.00282)	(0.00259)
$Credit_i * 1988$	-0.550**	0.203	0.205	0.00414	0.00303	-0.000260
	(0.234)	(0.209)	(0.192)	(0.00303)	(0.00260)	(0.00238)
$Credit_i * 1990$	-0.877***	-0.132	-0.0367	-0.00965***	-0.00439**	-0.00454**
	(0.198)	(0.186)	(0.166)	(0.00240)	(0.00199)	(0.00180)
$Credit_i * 1992$	-0.653***	-0.0781	0.0541	-0.00770***	-0.00361*	-0.00277
	(0.204)	(0.198)	(0.178)	(0.00242)	(0.00214)	(0.00193)
$Credit_i * 1994$	-0.924***	-0.470**	-0.296	-0.00981***	-0.00715***	-0.00574***
	(0.211)	(0.205)	(0.183)	(0.00241)	(0.00215)	(0.00194)
$Credit_i * 1996$	-0.769***	-0.646***	-0.398**	-0.00640***	-0.00670***	-0.00458**
	(0.229)	(0.231)	(0.199)	(0.00205)	(0.00210)	(0.00182)
$Credit_i * 1999$	0.0112	-0.0597	-0.100	-0.00101	-0.00114	-0.00111
	(0.215)	(0.207)	(0.200)	(0.00141)	(0.00143)	(0.00138)
$Credit_i * 2003$	0.709***	0.945***	0.668***	0.00562***	0.00731***	0.00547***
	(0.264)	(0.265)	(0.235)	(0.00189)	(0.00187)	(0.00170)
$Credit_i * 2005$	1.024***	1.272***	0.951***	0.00663***	0.00876***	0.00684***
	(0.291)	(0.292)	(0.274)	(0.00194)	(0.00187)	(0.00175)
$Credit_i * 2007$	1.106***	1.708***	1.569***	0.00546**	0.00980***	0.00920***
	(0.408)	(0.392)	(0.371)	(0.00246)	(0.00233)	(0.00223)
$Credit_i * 2009$	1.011***	1.289***	1.328***	0.00401*	0.00783***	0.00820***
	(0.347)	(0.360)	(0.335)	(0.00208)	(0.00211)	(0.00200)
Observations	432,252	432,252	432,252	432,252	432,252	432,252
R^2	0.790	0.831	0.851	0.861	0.894	0.906
Number of Villages	39,579			39,579		
Year FE	YES	NO	NO	YES	NO	NO
Village FE	YES	YES	YES	YES	YES	YES
Prov-yr FE	NO	YES	NO	NO	YES	NO
Amphoe-yr FE	NO	NO	YES	NO	NO	YES
Drop Outliers	YES	YES	YES	YES	YES	YES

This table reports the results of equation 11 on wages for the coefficient β_t. Standard errors clustered at tambon-level throughout.
*** p<0.01, ** p<0.05, * p<0.1

Figure 8: Fraction of Households with Migrants

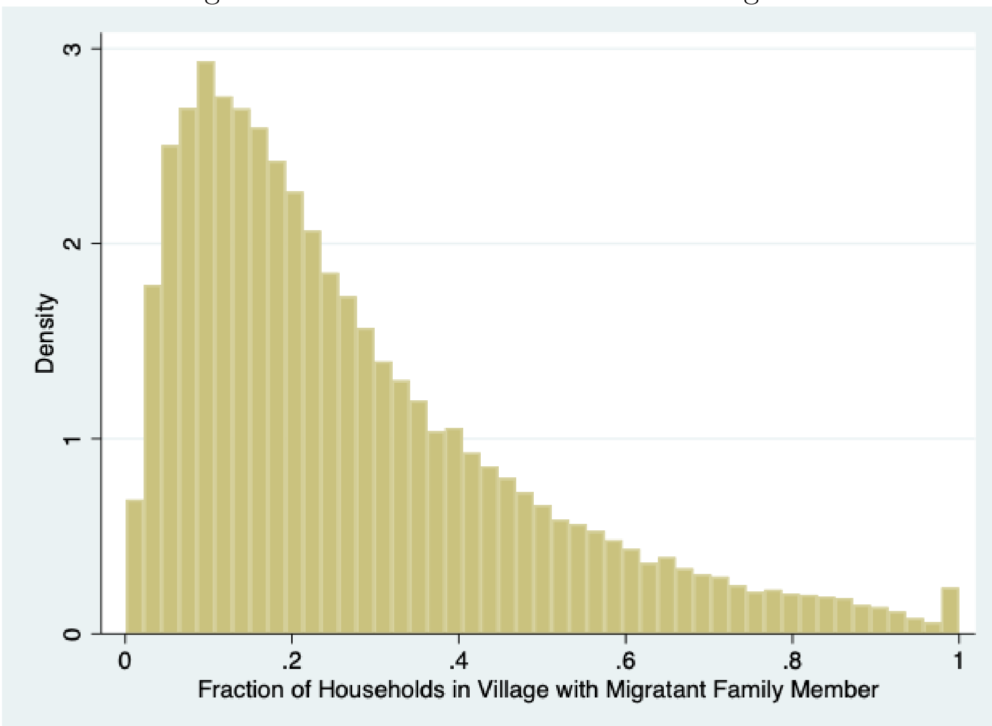


Table 11: Spillovers

VARIABLES	(1) Wage	(2) Wage	(3) Wage	(4) Log Wage	(5) Log Wage	(6) Log Wage
$\text{Credit}_i * \text{Post}$	0.913***	1.060***	1.110***	-0.00106	0.00739***	0.00853***
	(0.191)	(0.186)	(0.175)	(0.00174)	(0.00130)	(0.00121)
$\text{NeighborCredit}_{5,i} * \text{Post}$	3.238***	3.242***	0.955	0.0623***	0.0289***	0.0161**
	(0.991)	(1.054)	(1.042)	(0.00928)	(0.00757)	(0.00703)
Constant	38.70***			3.587***		
	(0.187)			(0.00280)		
Observations	432,252	432,252	432,252	432,252	432,252	432,252
R^2	0.790	0.831	0.851	0.861	0.894	0.906
Number of Villages	39,579			39,579		
Year FE	YES	NO	NO	YES	NO	NO
Village FE	YES	YES	YES	YES	YES	YES
Prov-yr FE	NO	YES	NO	NO	YES	NO
Amphoe-yr FE	NO	NO	YES	NO	NO	YES
Drop Outliers	YES	YES	YES	YES	YES	YES

This table reports the results of equation 2 on wages. Standard errors clustered at tambon-level throughout.
*** p<0.01, ** p<0.05, * p<0.1

Table 12: Isolation

VARIABLES	(1) Wage	(2) Wage	(3) Wage	(4) Log Wage	(5) Log Wage	(6) Log Wage
$\text{Credit}_i * \text{Post}$	0.842***	1.270***	0.889***	0.00367	0.00345*	0.00546***
	(0.321)	(0.289)	(0.259)	(0.00294)	(0.00199)	(0.00180)
$\text{Isol}_i * \text{Post}$	0.867***	0.306	0.402*	0.00841***	0.0104***	0.00592***
	(0.288)	(0.260)	(0.236)	(0.00260)	(0.00184)	(0.00166)
Constant	38.71***			3.587***		
	(0.187)			(0.00280)		
Observations	432,165	432,165	432,165	432,165	432,165	432,165
R^2	0.790	0.831	0.851	0.861	0.894	0.906
Number of Villages	39,569			39,569		
Year FE	YES	NO	NO	YES	NO	NO
Village FE	YES	YES	YES	YES	YES	YES
Prov-yr FE	NO	YES	NO	NO	YES	NO
Amphoe-yr FE	NO	NO	YES	NO	NO	YES
Drop Outliers	YES	YES	YES	YES	YES	YES

This table reports the results of equation 3 on wages. Standard errors clustered at tambon-level throughout.
*** p<0.01, ** p<0.05, * p<0.1

Table 13: Direct Effect on Population

VARIABLES	(1) Pop	(2) Pop	(3) Pop	(4) Log Pop	(5) Log Pop	(6) Log Pop
$\text{Credit}_i * \text{Post}$	4.447***	3.400***	2.438***	0.0452***	0.0377***	0.0313***
	(0.527)	(0.518)	(0.469)	(0.00348)	(0.00365)	(0.00363)
Constant	112.9***			4.534***		
	(0.411)			(0.00216)		
Observations	475,065	475,065	475,065	475,050	475,050	475,050
R^2	0.011	0.625	0.646	0.049	0.845	0.856
Number of Villages	39,593			39,593		
Year FE	YES	NO	NO	YES	NO	NO
Village FE	YES	YES	YES	YES	YES	YES
Prov-yr FE	NO	YES	NO	NO	YES	NO
Amphoe-yr FE	NO	NO	YES	NO	NO	YES
Drop Outliers	YES	YES	YES	YES	YES	YES

This table reports the results of equation 1 on population. Standard errors clustered at tambon-level throughout.
*** p<0.01, ** p<0.05, * p<0.1

Table 14: Inter-Village Trade and Capital Flows

	(1)	(2)	(3)	(4)
Panel A. Inter-Village Trade				
Trade Balance	-82.85	28.69	-79.95	-413.4
	(58.41)	(20.59)	(57.49)	(320.0)
Consumption Imports	1.214	13.26**	3.595	31.59
	(9.743)	(5.698)	(9.707)	(53.73)
Panel B. Inter-Village Capital Flows				
Net Factor Income Flows	-9.864**	0.699	-8.532*	-31.84
	(4.620)	(2.396)	(4.646)	(28.69)
Net Unilateral Transfers Flows	7.126	-0.887	6.746	38.55
	(8.576)	(2.598)	(8.598)	(46.47)
Net Financial Asset Flows	-27.08	-14.10*	-26.84	-114.5
	(20.23)	(7.833)	(20.51)	(99.33)
Net Cash Flows	111.4*	-18.35	106.6*	496.9
	(57.76)	(23.35)	(56.74)	(316.3)
Year FE	YES	YES	YES	YES
Village FE	YES	YES	YES	YES

Notes. This table reports the results of equation 1 on trade and credit flows between villages in the Townsend Thai Data. Reported values are for the coefficient on credit and standard errors are in parentheses. Each column uses a different measure of village size with columns (3) and (4) being our preferred specifications. In column (1), village size is the number of residential structures in the village. In column (2), village size is the number of residential structures with survey respondents. In column (3), village size is the number of non-empty residential structures. In column (4), village size is the number of residents. p-values are not adjusted for multiple hypothesis testing. *** $p<0.01$, ** $p<0.05$, * $p<0.1$