Enhanced Informal Networks:

Costly State Verification and the Village Fund Intervention*

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Abstract

Using data for over 600 households in 16 villages from Townsend Thai project, we find that the role of preexisting informal kinship networks in Thailand was enhanced following a quasi-formal village fund program in 2001. Transfers (gifts) among poor households play a crucial role in funding investment. This transfer mechanism and its role in investment were amplified for the poor households after the village fund, especially those with kinship ties. Moreover, we document a financial regime shift using maximum-likelihood estimation. Two exogenously incomplete regimes (saving only and lending/borrowing) dominated in the full sample and for the relatively poor before the village fund, but costly state verification, a less incomplete financial regime, dominates in the subsample of poor households following the village fund. The structurally-estimated cost of verification of the households with kinship is also significantly lower than the one without kinship after 2001, relative to before, suggesting the role of kinship was enhanced.

Keywords: Informal Network, Village Fund, Regime Shift, Costly State Verification

JEL: D10, E44, G10, L14, O10

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1. Introduction

Social and economic networks play essential roles in economies worldwide.[2] One specific interest in this context is the connection between the formal financial system and the role of informal networks. Prior studies have documented the role of informal lending channels when formal financial institutions are ineffective (e.g., Allen, Qian and Qian (2005); Banerjee and Duflo (2007)) or inaccessible (e.g., Hoff and Stiglitz (1990); Bell, Srinivasan and Udry (1997)). Likewise, results indicate that formal finance and information networks can be substitutes. Formal credit could crowd out the informal lending (e.g., Arrow (2000); Putnam (2000)). Authors Binzel, Field and Pande (2013) and Heß, Jaimovich and Schundeln (2018) document the decreased role of gift exchanges in the economy when formal financial access improves.

Other work suggests formal and informal mechanisms can be complements. Chandrasekhar, Kinnan and Larreguy (2018) pinpoint the role enforcement in informal networks, while Gine (2011), allowing both variation in enforcement and heterogeneity in transaction costs, finds evidence favoring the former. The much-cited work of Peterson and Rajan (1997) notes that larger firms on-lend finance acquired from formal sources via trade credit to smaller constrained firms, related to the Jain (1999) and Conning (2001, 2005) view of delegated monitoring.

Our paper here takes these results one step further. We find that informal kinship networks were activated with the advent of quasi-formal village funds, triggering increased gift-funded investment and the emergence of a costly state verification regime that had not been there previously.

[2] See, for example, Allen and Gale (2000), Jackson (2008), and Acemoglu et al. (2012) for seminal contributions and an extensive literature has followed.

More specifically, Thailand's Million Baht Village Fund implemented in 2001 was one of the biggest government direct credit programs worldwide, with a total of USD 1.8 billion initial credit injection covering virtually all of the villages in Thailand. The program's agenda is to provide government-subsidized credit to rural households, especially low-income households, to reduce inequality. Consequently, short-term credit flows to households jumped 41% following the 2001 village fund.[3] One can think of this as a formal or quasi-formal credit intervention with profound economic impacts.[4]

We primarily use the Townsend Thai monthly survey data in 16 villages of 4 provinces in rural areas of Thailand. The data contain a balanced panel with 616 households from 1999 to 2011.[5] We also use the Townsend Thai annual data for 64 villages in these same provinces as a robust check, with 758 households, the data set that is featured in earlier literature on village funds. We find in the monthly data that, for relatively poor households, transfers (gifts) through the informal kinship network plays a crucial role in funding investments, especially so after the 2001 village fund relative to their role before. In addition, the structural estimation shows that the village fund program induced a financial regime shift from exogenously incomplete regimes (saving only

[3] The program was initiated under the populist Prime Minister Thaksin Shinawatra, who was elected in January 2001 and funded by the central government. More specifically, the program was carried out by several government agencies such as the Community Development Department (CDD), and Bank for Agriculture and Agricultural Cooperatives (BAAC). There is a village fund committee with the full discretion of fund allocation within the village. Each village received one million baht (about $23,000) and allocated it across the village's households. On average, the loan size was $450, equivalent to 25% of the annual household income. The interest rate agreed to by village committees was 7% on average, much lower than the rates from other banks at the time (i.e., 11% on average).
[4] For example, Kaboski and Townsend (2012) documents that short-term credit flow for households jumped approximately 41% following the 2001 village fund, leading to increased consumption, agricultural investment, and income growth but decreased overall asset growth. Moreover, Banerjee et al. (2019) find that the program leads to increased profits and capital for the high TFP households while these positive effects are muted for households with low TFP. Jumps in the credit following the village fund are associated with higher capital and wealth and lower ROA gaps.
[5] The data starts in August 1998 so that we use 1999 as our first year. See the detailed data description in Section 4.a.

and lending/borrowing) before 2001 to a more complete regime, costly state verification, and imposing the costly state verification regime throughout, lower verification costs after.

The logic of the result is that shifting financial regimes can be costly, as in Greenwood and Jovanovic (1990), a model taken to data in Townsend and Ueda (2006) and Jeong and Towennd (2008). For more complete regimes to emerge, utility gains have to outweigh fixed costs of innovation/access. Our results are consistent with the view that the relatively large size of the village fund intervention, and the need for a better mechanism to allocate these funds, triggered a regime change. The Village Fund policy came as a surprise, and likewise, the transition comes suddenly.

We begin our analyses by using a variance-covariance decomposition to quantify the use of funding sources. We find an evident increase in the informal funding of household investment. Following Asdrubali, Sorensen, and Yosha (1996), we define a given household's deficit D in two ways; D=C-Q or D=C+I-Q, that is, with Q as net production profit, they vary with whether investments I are included in the deficit or only consumption C. There are numerous ways households can finance these deficits; deposit, lending and borrowing, gifts, and cash. Deficits will be the sum of all these financing sources: D=F_1+F_2+⋯+F n. All sources are observed in the Townsend Thai data, and the financial accounts are constructed to satisfy accounting identities. The measured use of gifts, that is, the median of cov(D,F)/var(D) of F for gifts is larger for all quartiles in the household cross-section than for any mechanism other than cash, larger than deposit, lending, and borrowing. Further, and the main point in this context, difference-in-difference analysis shows the role of gifts in financing the more comprehensive measure of the deficit, including investment, relative to the more narrow measure of the deficit with consumption only, is more pronounced after the village fund arrives in 2001 relative to what it was before. A statistical test is run on the median difference.

We further explore the mechanism by distinguishing households with family-related households in the village versus those who have none. Specifically, we count the number of kinship connections across households based on whether a household's parents, siblings, adult children, and parents' siblings live in the same village or not. For the full sample, the number of such kinship connections ranges from 0 to 16, with the average number of kinships as 2.7. As a percentage, 18.49% of the households have zero kinship connections. We find that gifts are essential in financing the more comprehensive measure of deficits with investment for households with kin vs. households without kin, more so following the village fund program in 2001 relative to before.

Next, we provide a structural interpretation, being yet more specific about the mechanism, thought the lens of theory interacted with the data.[6] Using the survey panel data for household-level consumption, production, investment, and capital stock, we compare four financial regimes: two exogenously incomplete regimes (i.e., saving only and lending/borrowing) and two relatively more complete ones (e.g., moral hazard with unobserved effort and costly state verification, CSV). In particular, we structurally estimate those dynamic models by maximum-likelihood estimation and statistically test them against each other by Vuong test (Vuong (1989)).

As in previous work, Karaivanov and Townsend (2014), the lending/borrowing regime dominates other regimes in the full sample over all households and all-time intervals from 1999 to 2011. However, again, there is a change after the million-baht fund program in 2001. In particular, and more interestingly for this paper, when we restrict the sample to the bottom 25% relatively

[6] This adds to the growing but yet limited studies combining the structure model and the randomized controlled trial (e.g., Attanasio, Battistin and Mesnard (2012); Todd and Wolpin (2006); Kaboski and Townsend (2011); Lagakos, Mobarak and Waugh (2018); Meghir et al. (2019)).

poor households according to initial wealth in 1999, and stratify the sample into pre and post village fund periods (e.g., 1999 to 2001 vs. 2002 to 2011), we find that while savings only and lending/borrowing regimes are tied and dominate the other regimes for 1999 to 2001, for the bottom 25% poor households, the CSV model dominates after, from 2002 to 2011.[7]

For these poor households, risk-sharing plays an essential role, as is already evident in the discussion of gifts and smoothing, though subject to obstacles. In the structural costly state verification model, the cost of verifying otherwise unobserved income/output is a key variable, an obstacle to risk-sharing and placing funds. However, in extreme cases, when verification is free (i.e., zero verification cost), it is always optimal to audit agents, whether done by a "principal" or community as a whole. In this case, the CSV financial information regime is essentially the full information full risk-sharing investment model with fully observed income, if there are no other obstacles in smoothing consumption and financing investment. On the other extreme, when the verification cost is exceptionally high, the community would virtually never audit agents and can never verify or know the true production from the agent. This is a hidden output financial regime. We thus study the extent of risk-sharing and financing among households by estimating the key verification cost for various subsamples and over different time intervals.

The story of the enhancement of the informal network is indeed echoed through the CSV model. The analysis shows that having kin in the village is associated with significantly lower verification costs after 2001 relative to the period before the village fund arrived. Specifically, the verification cost is an estimated parameter with standard error for each of the various stratifications,

[7] In contrast, for the top 25% wealthy households, there is no detectable shift; simple lending/borrowing always fits the best for that group over time. Those richer households, who are active financial market participants, lend more or less as their output varies. However, the implementation after the village fund would be different. Before 2001, they are engaged in simpler lending transactions. After 2001 they are likely on the other side of CSV borrowing, pooling savings as if into a mutual fund, though mechanically this happens though lending chains, as in Sripakdeevong and Townsend (2019). Richer households are also borrowing some of the time, but evidently less engaged in more sophisticated state verification when they borrow.

households with and without kin, for 1999-2001 and 2002-2011. We test for a statistically significant difference in difference, kin versus non-kin before and after. The kinship network is activated after the village fund in the sense of displaying relatively lower verification costs. There is indeed some evidence that networks were activated, not simply enhanced. For the pre-village fund period, the verification cost κ is 0.014 for the households with kinship, which is larger than the κ (0.004) without kinship (though this must be taken with a grain of salt as CVS is not the most dominate regime for the pre-village fund period). In contrast, the verification cost is lower after village fund for households with kinship connections (κ equals 0.34 and 0.01 for unconnected and connected households, respectively), allowing risk sharing and investment as a function of observed output (and again after the fund comes in, this is the statistically dominant regime after). Even more specifically, if we identify households connected to individuals on the village fund committee responsible for allocation of the funds, connected through kin, verification costs are significantly lower for those with such kin paths than those without such paths after the village fund relative to before.[8]

Many studies have shown that risk-sharing is key to the economic development (e.g., Rosenzweig (1988); Townsend (1994; 1995); Udry (1994); Morduch (1995); Jack and Suri (2014)), and that social and financial networks can serve as tools to enhance risk-sharing (e.g., Jackson, Barraquer and Tan (2012); Kinnan and Townsend (2012); Ambrus, Gao and Milán (2017); Ambrus and Elliott (2018); Chandrasekhar, Townsend and Xandri (2019); Meghir et al. (2019)).

[8] The DID is equal to difference of κ for unconnected and connected households post-village fund minus this difference pre-village funds, which is ((0.337-0.014) - (0.014-0.004)) = 0.335 at the 1% significant level. In our numerical analysis, we normalize the data by the 90th quantile of households' capital levels. The verification cost of 0.335 is economically significant, which equals 33.5% of the 90th quantile of households' capital level.

Our findings for verification costs complement these studies by documenting the fundamental role of informal networks in facilitating resource allocation.

Furthermore, we connect back to the annual data, the original Thai village fund studies for 64 villages. The quasi-experimental evidence distinguishes small vs. larger village populations, as each village got one million baht, regardless. Using median village size, we estimate verification costs for small versus large villages after village fund relative to before, again focusing on relatively poor households, as guided by the monthly data analysis above. There is again some evidence of network activation, as for the pre-village fund period from 1997 to 2001, the verification cost parameter is higher for these households in small villages (0.283) than the ones in large villages (0.059) whereas following the village fund from 2002 to 2007, it is the other way around, the verification cost is significantly higher for households in larger villages (0.276) than small villages (0.150). This difference in difference is -0.35 ((0.150-0.276)-(0.283-0.059)), which is statistically significant at the 1% level.

Finally, we stratify households in the annual data by their initial TFP level in 1997 and structurally compare financial regimes. For high TFP households, we find regime shifts similar to those for poor households in monthly data. Specifically, during the pre-village fund period (i.e., 1997 to 2001), the lending/borrowing regime dominates for high TFP households. The dominant regime changed to CSV for the post-village fund period (i.e., 2002 to 2007) for those high TFP households. In contrast, for low TFP households, we do not observe such regime shifts.

These findings in annual data echo Banjeree et al. (2019), which find that the village funds were not allocated according to initial productivity; that is, productivity estimated in pre-intervention data interacts with the inverse village size as an instrument for per capita treatment and this variable is not significant. Hence both low and high productivity households got funds.

Yet, with the same instrument specification, high productivity households increased investment and had higher levels of capital and profits with the advent of village funds. This is consistent not only with a direct allocation effect among those fortunately connected enough to get funding but also an indirect effect through networks. Finally, short-term non-program credit increased for these high productivity households. As in Banerjee et al. (2014), though microfinance crowds out informal finance for novices, complementarities are observed for seasoned entrepreneurs.

Moreover, our results are consistent with scattered results in earlier literature and in on-going work, though previously, the dots had not been connected. There is evidence in Vera-Cossio (2019) that relationship links to members of the village fund allocation committee played both a direct role in securing funds, but also an indirect role, a tiered allocation of credit through family connections. Indeed we used these very same kinship paths in sample stratifications for the costly state verification regime.

In addition, Sripakdevong and Townsend (2019) show that interest rates are significantly higher for village fund loans to households unconnected to the kinship network. Further, villages reorganized themselves to systematically enhance previously existing credit-refinancing-chains by setting aside funds to roll-over loans. From risk-sharing regressions, reduced form transaction costs are shown to be lower for participants in these chains, relative to those not participating, despite higher risk aversion for such households. Our present paper here gives an interpretation of what these transaction costs are, linking them through the CSV model to lower costs of state verification. Put the other way, the role of informal kinship networks is enhanced to mitigate frictions, taking the form of decreased verification costs in kinship networks. Relatedly, Sripakdevong and Townsend (2019) show that households borrow in order to relend and that early repayment reverberates back along these lending/credit chains.

2. Data and Analysis

2.1. Data Description

We use two datasets from the Townsend Thai survey. Most of our analyses are based on the monthly survey data from 1998 to 2011 in 16 villages from 4 provinces in rural Thailand. Since the data start in August 1998, we use 1999 as our first year. Based on the monthly data, we aggregate across months to deliver annual data, as in Karaivanov and Townsend (2014). We use the balanced panel with 616 households, which records the variables in granular household financial accounts such as consumption, capital, production, and investments. We also observe the kinship connections for each household; we identify who is related to whom and build the informal kinship networks based on that.[9] Since our focus is on costly state verification, we only pick the households with farm and non-farm business. We define the capital as agriculture assets and business assets and exclude the households with zero capital in these activities. We end up with a total of 532 households.

The second dataset is the annual survey in Townsend Thai data from 1997 to 2007. It covers 960 households in 64 rural and semi-urban villages across the same four provinces of Thailand. This allows us to explore the variation across villages with different sizes. The production q is cash flow from production, revenue less expenses. The depreciation rate on capital is 5%, and we calculate the investment as $k' - 0.95 \times k$. We adjust for inflation for all variables.[10]

2.2. The Role of Informal Network

Based on the data, we start the analyses by exploring the role of informal networks in financing households' consumptions and investments. In particular, we explore the mechanics under the

[9] We employ the same method to build the kinship network, as in Kinnan and Townsend (2012) and Samphantharak and Townsend (2018).
[10] We obtain the inflation data from the Bureau of Trade and Economic Indices, Ministry of Commerce in Thailand.

value flows to poor households. In particular, how do they get external funding for investment? What are the financial frictions? Does the kinship network play a role?

More specifically, we first look at the role of gifts and other smoothing mechanisms, how the deficit created by the gap household consumption plus investment less production income is financed. We use a variance-covariance decomposition following Asdrubali, Sorensen and Yosha (1996). Specifically, we define the households' deficit in two ways: 1) the deficit is equal to consumption plus investment minus the net production profits (i.e., D=C+I-Q); 2) the deficit is equal to consumption minus the net production profits only (i.e., D=C-Q). The difference obviously emphasizes the investment part. Here are several ways for the households to finance these deficits; their deposit, lending and borrowing, gifts, and cash. D will equal given the construction of the data, the sum of all these financing sources: $\mathrm{D} = F_1 + F_2 + \cdots + F_n$. In the variance-covariance decomposition, we have:

$$1 = \frac{cov(D, F_1)}{var(D)} + \cdots + \frac{cov(D, F_n)}{var(D)}$$

Each of these objects can be found by running OLS regressions of the smoothing mechanism onto the deficit, one mechanism as one regression at a time. Thus, for each financing source F, we calculate its contribution to the total variance in D as $\mathrm{cov}\ (\mathrm{D}, \mathrm{F})/\mathrm{var}(\mathrm{D})$. Table 1 shows the results under the two different definitions of D. In columns (1) to (3), we define the deficit including the investments (i.e., $\mathrm{D} = \mathrm{C} + \mathrm{I} - \mathrm{Q}$) and report the value of $\mathrm{cov}(\mathrm{D}, \mathrm{F})/\mathrm{var}(\mathrm{D})$ for each financing source on the first, second, and third quartiles, respectively. We find that gifts and use of cash are the two most essential tools to finance these households' deficits.

In particular, Panel A is for the pre-village fund period. In column (3), the median of $\mathrm{cov}(\mathrm{D}, \mathrm{F})/\mathrm{var}(\mathrm{D})$ for gifts is 4.60%. Other devices such as deposit, lending and borrowing, and ROSCA have much smaller shares in the variance-covariance decomposition analysis. Borrowing appears but is lower than might have been anticipated. Lending as a category is even smaller though this may be understated in the actual data. However, note that the analysis includes negative deficits, i.e., a relatively rich household runs a surplus and smooths this by giving out gifts.[11]

In columns (4) to (6), we exclude investments from deficit (i.e., $\mathrm{D} = \mathrm{C} - \mathrm{Q}$). Again, gifts and cash are the two most important tools to finance these households' deficits, while gifts play a smaller role relative to columns (1) to (3) when we did include investments in deficit. For example, in column (5), the median of $\mathrm{cov(D, F)/var(D)}$ for gifts is 3.18%, which is 1.42 percentage points lower than the 4.60% in column (2) (though in this case statistically insignificant with Z-stats of 0.468 in the test for median differences).

Next, we repeat the same analyses in Panel B for the post-Village Fund period (i.e., 2002 to 2011). First, gifts play a much larger role in the post village fund period than the pre-Village Fund period. For example, in column (2) of Panel B, the $\mathrm{cov(D, F)/var(D)}$ for gifts is 16.64% that is much larger than the 4.60% in Panel A. Furthermore, during the post-village fund period, the role of gifts in financing household deficit is enhanced. In particular, in column (5) of Panel B, the $\mathrm{cov(D, F)/var(D)}$ for gifts is 9.76%, which is approximately 6.88 percentage points lower than 16.64% in column (2).

Next, we perform a difference-in-differences (DID) calculation to compare the role of gifts for investments before and after the village fund. In particular, as shown in Panel A, the $\mathrm{cov(D, F)/var(D)}$ for gifts is approximately 1.42 percentage points larger for D with investments, while in Panel B, the $\mathrm{cov(D, F)/var(D)}$ for gifts is approximately 6.88 percentage points larger for D with investments. This difference between pre- and post-village fund periods in the

[11] Table A2 in the Appendix repeats the variance-covariance decomposition for the whole sample period (i.e., 1999 to 2011) for the richest 25% and poorest 25% households, respectively. Gifts still play an essential role in households' finance. Moreover, gifts are particularly crucial for relatively poor households, especially for funding investment.

$\mathrm{cov}(D,F)/\mathrm{var}(D)$ for gifts is approximately 5.46 percentage points at the 1% significance level (i.e., 6.88-1.42). This suggests that gifts exchange is important to finance household investments, especially after the 2001 village fund.

[Place Table 1 about here]

To further strengthen the linkage between the gifts and informal network, we stratify the sample into the households with kinship connections vs. the households without. In particular, we use the kinship network data in the Townsend Thai monthly survey to stratify the data into two subsamples: households related to other households in the village by kinship and those without. Specifically, we count the number of kin based on whether the households' parents, siblings, adult children, and parents' siblings live in other households but in the same village. For the full sample, the number of kin ranges from 0 to 16. As a percentage, 18.49% of the households have no kin, while the average number of kinship connections is 2.7.

We use the deficit with investments, and Table 2 shows the results. Columns (1) to (3) are for the households with kinship connections, and columns (4) to (6) are for the households without kinship connections. Panel A is for the pre-village fund period. In column (2), the median $\mathrm{cov}(D,F)/\mathrm{var}(D)$ for gifts is 4.06% for the households with kinship connections, while in column (5), the median $\mathrm{cov}(D,F)/\mathrm{var}(D)$ for gifts is 20.05% for the households without kinship connections. The difference is statistically insignificant (i.e., z-stats is 0.9606). In contrast, Panel B is for the post-village fund period, the median $\mathrm{cov}(D,F)/\mathrm{var}(D)$ for gifts is 18.13% for the households with kinship connections, while the median $\mathrm{cov}(D,F)/\mathrm{var}(D)$ for gifts is 6.38% for the households without kinship connections. The difference is 11.75 percentage points, which is statistically significant at the 10% level (i.e., z-stats is 2.94). We again calculate the DID of the

$\text{cov}(D, F)/\text{var}(D)$ for gifts between the households with kinship vs. without kinships and before and after the village fund in 2001. The number is 27.74 percentage points at the 5% significance level.

These findings in Table 2 suggest that for households with other families in the village, gifts are more important to finance household investment than the households without other families following the village fund program in 2001. In other words, kinships facilitate gift exchange among households in facilitating investment projects.

[Place Table 2 about here]

In summary, gifts are one of the most critical financial smoothing mechanisms of rural households. Gifts are used not only for risk-sharing but also for investment financing. Our conjecture is that households use gifts to channel funds among themselves to fund investment opportunities. In addition, this informal network's role is statistically enhanced following the formal government credit program, i.e., the 2001 village fund.

2.3. Structure Estimation for Financial Regimes

In this section, we employ structural estimation to study further the financial regimes underlying households' finance. In particular, we compare the four financial regimes: savings only (autarky), lending/borrowing, moral hazard, and costly state verification, CSV by fitting each regime to the data of the households in Townsend Thai monthly survey, then testing to see if the differences are statistically significant.

2.3.1. Structural Models

We employ the same models for the savings only, lending/borrowing, and moral hazard regimes as in Karaivanov and Townsend (2014).[12] The dynamic model of costly state verification, which we focus on here, is an extension of the Karaivanov and Townsend (2014) hidden output regime (HO); the principal cannot observe the production outcome of agents unless a costly audit occurs, as in Townsend (1994). A risk-neutral principal as a stand-in for the community as a whole maximizes its value function V at each period given a previously promised utility ω for the agent and the agent's preexisting capital by transferring τ as a function of output in the current period and promising utility for the next period. We define an agent's consumption $C = q + \tau + (1-\delta)k - k'$, where q is the output from the agent, τ is the transfer from the principal to the agent (which can be negative), k is current capital, k' is capital next period, and δ is the rate of depreciation. The utility function of the agent is the CES form:

$$\mathrm{U(c,z)} = \frac{c^{1-\sigma}}{1-\sigma} - z^{\theta}$$

Parameter σ is risk aversion, and parameters θ is the curvature in the disutility of effort. The variable z is the agent's effort, which enters the agent's production function and as disutility into the agent's preferences.

A truth-telling constraint, derived via the revelation principle as in Townsend (1988), ensures it is always optimal for an agent to tell the truth about realizations of its initial output q. Furthermore, under CSV, if the agent were to lie about the production and get caught under an audit, the penalty is a zero current period consumption and staying at the autarky regime forever.

[12] The programming problems used in our study are as written in Karaivanov and Townsend (2014), page 894-900.

This makes the right-hand side of the truth-telling constraint, under a deviation, particularly harsh and helps facilitate truth-telling.

In summary, the state variable and the contemporary state vector for the agent is k and ω. The choice variable vector for the principal is τ, q, z, k′, ω′, d, where ′ denotes next period and d=0 under no auditing, and d=1 under auditing. Audits can be random, to economize on costs. We also assume that the agent pays the verification costs in the equilibrium. We employ the linear programming approach that is introduced by Prescott and Townsend (1984) and Phelan and Townsend (1991) to maximize the value function of the principal. In particular, we model the financial contracts as lotteries π over choice variables (e.g., τ, q, z, k′, ω′, d), and the principal maximizes the value function, discounted expected present value of profits as in equation (1):

$$\mathrm{V}(\mathrm{k}, \omega) = \max_{\tau,q,z,k',\omega',d} \sum \pi(\tau, q, z, k', \omega', d|k, \omega)\left[(-\tau) + \frac{1}{R} \times \mathrm{V}(\mathrm{k}', \omega')\right], (1)$$

The maximization subjects to promise-keeping constraint as in equation (2),

$$\sum_{\tau,q,z,k',\omega'} \pi(\tau, q, z, k', \omega', d = 0|k, \omega)[U(q + \tau + (1 - \delta)k - k', z) + \beta\omega']$$

$$+ \sum_{\tau,q,z,k',\omega'} \pi(\tau, q, z, k', \omega', d = 1|k, \omega)[U(q + \tau + (1 - \delta)k - k' - \kappa, z) + \beta\omega'] = \omega, (2)$$

and the truth-telling constraint as in equation (3), $\forall(\bar{z}, \bar{q}, \hat{q} \neq \bar{q} \in \mathrm{Z} \times \mathrm{Q} \times \mathrm{Q})$

$$\sum_{\tau,k',\omega'} \pi(\tau, \bar{q}, \bar{z}, k', \omega', d = 0|k, \omega)[U(\bar{q} + \tau + (1 - \delta)k - k', \bar{z}) + \beta\omega'] +$$

$$\sum_{\tau,k',\omega'} \pi(\tau, \bar{q}, \bar{z}, k', \omega', d = 1|k, \omega)[U(\bar{q} + \tau + (1 - \delta)k - k' - \kappa, \bar{z}) + \beta\omega'] \geq$$

$$\sum_{\tau,k',\omega'} \pi(\tau,\hat{q},\bar{z},k',\omega',d=1|k,\omega)[U(0,\bar{z})+\beta\Omega(\mathrm{k})]+$$

$$\sum_{\tau,k',\omega'} \pi(\tau,\hat{q},\bar{z},k',\omega',d=0|k,\omega)[U(\bar{q}+\tau+(1-\delta)k-k',\bar{z})+\beta\omega'], (3)$$

It also subjects to probability technological constraints of π as in equations (4) and (5):

$$\sum_{\tau,k',\omega',d} \pi(\tau,\bar{q},\bar{z},k',\omega',d|k,\omega)=P(\bar{q}|\bar{z},k)\sum_{\tau,q,k',\omega',d} \pi(\tau,q,\bar{z},k',\omega',d|k,\omega), \forall \bar{q},\bar{z}\in Q\times Z\,, (4)$$

$$\sum_{\tau,q,z,k',\omega',d} \pi(\tau,q,z,k',\omega',d|k,\omega)=1\,, (5)$$

where Ω is the value function under autarky. We assume that if the agent lies, and this is revealed in an audit, the penalties are zero consumption in the current period and that the agent stays in the autarky regime forever. When agents go back to autarky, the initial capital is k.

The production function is stochastic, and P(q|z,k) is the probability of output level q when inputting effect z and capital k. We use the parametric function to calculate the probability distribution of q in equations (6) and (7):

$$\mathrm{P}(\mathrm{q}=q_1|\mathrm{z},\mathrm{k})=1-(\eta k^{\rho}+(1-\eta)(1-z)^{\rho})^{\frac{1}{\rho}}, \qquad (6)$$

$$\mathrm{P}(\mathrm{q}=q_i|\mathrm{z},\mathrm{k})=\frac{1}{\#Q-1}(\eta k^{\rho}+(1-\eta)(1-z)^{\rho})^{1/\rho} \text{ for i} = 2,\dots,\#\mathrm{Q}, (7)$$

We use the actual data in Townsend Thai monthly survey of production, capital, and effort to fit the parametric production functions above. In this model, we assume that agents pay the verification cost κ. In this manner, we can place a boundary on κ, which should not exceed the agent's production. Eventually, the principle also bears the costs via τ. However, zero consumption will give us negative infinite utility value under the CRRA utility function. To deal with this, we use a close-to-zero positive number for consumption in our numerical analysis.

Finally, we note that the estimated parameter κ could be quite large, in which case audits rarely occur if ever, and the CSV model reduces to the unobserved output as in Karaivanov and Townsend (2014), page 953-954. Conversely, for most levels of κ, costly audits do happen, as we find in the model generated data, and especially when κ is low. In particular, when κ is virtually zero, audits take place virtually all time. Hence, the output is virtually fully observed, so there are no obstacles, and we have a full risk-sharing regime.

Next, we select the grids for the variables k, q, and c from the histograms in the data. For example, grid K has 5 numbers, which are the 10^{th}, 30^{th}, 50^{th}, 70^{th}, and 90^{th} quantile of the capital data across households. Due to dimensionality and computational limitations, we select 5 grid points of k, q, and ω. For consumption c, we have 30 grids. We also include the measurement error in the data, assumed to be additive and distributed as $\mathrm{N}(0, (\gamma_{me} r(x))^2)$. Here r(x) is the range of grid X, which equals $x_{max} - x_{min}$. The state variable ω as promised utility is, of course, unobserved, and we assume it has a normal distribution $\mathrm{N}(\mu_\omega, \gamma_\omega^2)$.

We solve the optimal lotteries π to maximize the value function in equation (1) under each information financial regime. We maximize the log-likelihood of the data on consumption, capital, investment, and production to estimate our key parameters: γ_{me}, σ, θ, $\mu_\omega, \gamma_\omega$, and κ. (the less negative the likelihood, the better the fit). After we get the MLE results from the four regimes, we use the Vuong test to select the best fitted one or report ties.

2.3.2. Regime Comparison

Following Karaivanov and Townsend (2014), we first perform the MLE and Vuong test based on the entire household sample from 1999 to 2011 and find results consistent with previous reports in the literature. Specifically, Table A5 in the Appendix shows that, for all households in our data, the lending/borrowing regime statistically dominates the other regimes. For example, the MLE is -5.25 for the lending/borrowing regime while it is -5.71 for the CSV, and the Vuong test shows the difference between the two is statistically significant at the 1% level (i.e., z-stat is 9.52). Although these regime findings are similar to that of Karaivanov and Townsend (2014), which use the same monthly survey from 1999 to 2005, the estimation results are different since we use a longer period here, i.e., from 1999 to 2011.[13]

Next, we stratify the sample into poor and rich households based on their initial wealth distribution in 1999. In particular, we sort the households based on their net wealth in 1999 and select the poorest 25% of them. Based on these subsamples, we repeat the MLE and Vuong tests. Table 3 shows the results for the bottom 25% of households. Panel A shows that for the pre-village fund period (i.e., 1999 to 2001), the savings only and lending/borrowing regimes are tied and dominate the other remaining regimes. In particular, the MLE for CSV is -7.52 while it is -6.32 for the lending/borrowing regime. The Vuong test shows that the difference between the two is statistically significant at the 1% level (i.e., z-stat is 16.61). Panel B is for the post-village fund period (i.e., 2002 to 2011) and shows a regime shift. Specifically, from 2002 to 2011, the CSV regime dominates the other regimes. The MLE for CSV is -6.29, while it is -6.41 for the

[13] To verify the linear programming model, we simulate the data with the pre-determined true parameters of the CSV model. Then, we use the simulated data to fit four regimes and estimate the parameters in each regime. Table A4 in Appendix shows that our algorithm are able to pick the true financial regime (i.e., CSV), and the estimated parameters are close to the true parameters.

lending/borrowing regime. The Vuong test shows that the difference between the two is statistically significant at the 1% level (i.e., z-stat is 4.86).

[Place Table 3 about here]

In the Appendix, we repeat the analyses of Table 3 but on the subsample of the 25% richest households. Table A1 shows the results. We find consistent with the results for the whole sample in Table A5 that wealthier households best fit the lending/borrowing regimes. Specifically, the lending/borrowing regime dominates others in both the pre- and post-village fund periods.

In short, these findings suggest that there is heterogeneity across households regarding the financial regimes. Risk-sharing plays an essential role among poor households, though subject to obstacles, verification of output, and costs. The verification cost of 0.172 is substantial. The richer households are active financial market participants, lending more or less as their output varies. They are likely on the other side of CSV borrowing; one can think of them as pooling savings as in a mutual fund. Richer households are also borrowing at times, but evidently less engaged in more sophisticated state verification when they borrow.

2.3.3. Informal Networks and the Verification Costs

As noted earlier, the verification cost is a key variable in the CSV model, and a positive number is an obstacle to risk-sharing. In extreme cases, when verification is free (i.e., zero verification cost), it is always optimal for the principle to audit agents. In this case, the CSV regime is essentially the full information model. On the other hand, when the verification cost is exceptionally high, the principle would never audit agents and can never verify or know the true production from the agent. It is equal to the hidden output regime. We study risk-sharing and financing among households by estimating the verification costs for various subsamples, and over different periods.

Since the CSV dominates other regimes on the poorest 25% households, we study the verification cost for these households with and without kinships in the village. For this bottom 25% strata of households, the number of kinship connections ranges from 0 to 10. In particular, we randomly select the data for consumption, investment, production, and capital repeatedly with replacement; and estimate the κ in the CSV structure model with standard errors for each group.

Table 4 Panel A shows the results. Panel A is for the pre-village fund period, and Panel B is for the post-village fund period. For example, in Panel B, the κ for households with zero kinships is 0.34 while it is only 0.014 for the households with kinship relationships among households, from at least one related household to at most ten related households.[14] In terms of the economic magnitude, 0.34 is a fairly large number. For example, the 70^{th} and 90^{th} in grid K are 0.183 and 1, respectively. This suggests that the verification cost of 0.34 is above the 70 percentile of the households' capital. With kinship, the low verification cost makes audits easier, facilitating the credit flows and more risk-sharing. Our finding that kinship is associated with lower verification cost is consistent with the enhanced role of kinship in the variance-covariance decomposition results, that is, the lower the cost, the greater the role.

Further, we formally compare the role of kinship before and after the village fund. In particular, Panel A shows that κ for households with zero kinship is 0.014 while it is only 0.004 for the households with kinship relationships. The difference in κ is approximately 0.0097, which is

[14] We tried other stratifications based on different cut-offs on the number of kinship connections. We find that the primary contrasts are between the households with and without kinships. In Table A3, we consistently find that the verification costs are lower for households with kinship for the whole sample period from 1999 to 2011.

statistically significant. However, this difference in κ in Panel A for the pre-village fund period is much smaller than that in Panel B. We calculate the DID in κ between the households with and without kinship and before and after the village fund in 2001. The DID is approximately 0.3129 (0.3227-0.0097) at the 1% significance level (T-stats is 48.58). These comparisons of κ suggest that the 2001 village fund enhanced the role of the informal kinship network among households, as evidenced by lower verification costs.

[Place Table 4 about here]

To further verify the role of the 2001 village fund, we restrict informal kinship connections to these households with kinship links to the village fund borrowers. We find consistent results, as shown in Table 5. Panel A shows that from 1999 to 2001, the verification cost is significantly higher for the households connected to the village fund borrowers (i.e., κ=0.165) than the households without such connections (i.e., κ=0.01). The difference in κ is -0.154, which is statistically significant at the 1% level (i.e., t-stat=-415). In contrast, Panel B shows that from 2002 to 2011, the verification cost parameter is significantly lower for the households connected to the village fund borrowers (i.e., κ=0.073) than the households without such connections (i.e., κ=0.73), almost ten times larger. The difference in κ is 0.660, which is statistically significant at the 1% level (i.e., t-stat=2486). Again, we perform the DID calculation, and the mean DID of κ between the households with and without kinship connections to the village fund borrowers before and after the village fund is 0.814, which is statistically significant at the 1% level (i.e., t-stat=1795).

[Place Table 5 about here]

2.3.4. Annual Data Analysis

Lastly, we connect the results from monthly data to the Townsend Thai annual survey on the households in 64 villages from 1997 to 2007. Kaboski and Townsend (2012) studied the effects of the village fund program using as an instrument for per-capital treatment, the inverse number of households found to be largely exogenously. With one million baht of credit regardless of village size, per capita treatment is higher for small villages. We employ a similar method by stratifying the villages into small vs. large ones by median village size. We then compare the κ in the CSV regime between the small and large villages.

Table 6 shows the results. Panel A is for the pre-village fund period (i.e., from 1997 to 2001), Panel B is for the post village fund (i.e., from 2002 to 2007). The DID of κ between the households in the small vs. large villages before and after the village fund is -0.35, which is statistically significant at the 1% level (i.e., t-stat=30.98). These findings are consistent with the role of the informal network being amplified (i.e., lower verification costs) for households in small villages who receive more credit than households in larger villages where per capita treatment was low.

[Place Table 6 about here]

In addition, we stratify the households into low and high TFP groups in the annual data sample. In particular, we calculate the TFP for each household in 1997 as the productivity measure following (Banerjee et al. (2019)). We use the median of the TFP to select a sample of high TFP households. Those households have more investment opportunities, and the formal credit program should impact them more than the low TFP households. In Table 7, we compare the four financial regimes before and after the 2001 village fund program, respectively. In Panel A, the lending/borrowing regime dominates others from 1997 to 2001 pre village fund. In contrast, Panel B shows a regime switch from 2002 to 2007, as now the CSV regime dominates others for this post-village fund period. This is consistent with our findings in Table 3. This echoes Banerjee et al. (2019), which finds that the program leads to increased profits and capital for the high TFP households while these positive effects are muted for the households with low TFP. Our findings suggest that the enhanced informal kinship network reduced financial frictions (i.e., verification costs), allowing financing of the good investment opportunities among the poor households.

[Place Table 7 about here]

3. Conclusion

In this paper, we document novel and essential interactions between informal networks and formal credit programs regarding household finance and investment. We find that poor households in rural Thailand switched from a lending/borrowing information financial regime to a costly state verification regime following a massive government credit program (i.e., 2001 village fund). We find suggestive evidence that credit flows among household kinship networks in the form of gifts exchange, which finance the poor households' investments, especially after the 2001 village fund. Moreover, the verification costs parameter in the CSV regime is significantly lower for the households connected to the informal kinship network than for unconnected households following the village fund program. The role of the informal network was enhanced following the formal village fund program.

The reinforcement between formal and informal lending channels in rural Thailand has significant economic impacts. It helps the poor households to take advantage of investment opportunities, channeling the fund from the village fund borrowers to more productive poor households. Arguably, this fueled the growth of poor households' wealth and reduced inequality.

References

Acemoglu, D., V. M. Carvalho, A. Ozdaglar, and A. Tahbaz-Salehi (2012). The network origins of aggregate fluctuations. *Econometrica,* 80, 1977–2016.

Allen, F., and D. Gale (2000). Financial contagion. *Journal of political economy*, 108(1), 1-33.

Allen, F., J. Qian, and M. Qian (2005). Law, finance, and economic growth in China. *Journal of Financial Economics*, 57-116.

Ambrus, A., and M. Elliott (2018). Investments in social ties, risk sharing and inequality. *Working paper*.

Ambrus, A., W. Y. Gao, and P. Milán (2017). Informal Risk Sharing with Local Information. *Working paper*.

Arrow, K. J. (2000). Observations on social capital. Social capital: A multifaceted perspective. *World Bank Publisher*, 6, 3–5.

Asdrubali, P., B. E. Sorensen, and O. Yosha (1996). Channels of Interstate Risk Sharing: United States 1963–1990. *The Quarterly Journal of Economics*, 1081-1110.

Attanasio, O., E. Battistin, and A. Mesnard (2012). Food and Cash Transfers: Evidence from Colombia. *The Economic Journal*, 92-124.

Banerjee, A. V., and E. Duflo (2007). The Economic Lives of the Poor. *Journal of Economic Perspectives*, 141-168.

Banerjee, A., E. Breza, R. M. Townsend, and D. Vera-Cossio (2019). Access to credit and productivity: Evidence from Thai Villages. *Working Paper*.

Banerjee, A., E. Breza, E. Duflo, and C. Kinnan (2014). Does Microfinance Foster Business Growth? The Importance of Enterpreneurial Heterogeneity. *Working paper.*

Banerjee, A. V., A. G. Chandrasekhar, E. Duflo, and M. O. Jackson (2019). Changes in Social Network Structure in Response to Exposure to Formal Credit Markets. *Working Paper.*

Bell C., T. N. Srintvasan, and C. Udry (1997). Rationing, spillover, and interlinking in credit markets: the case of rural Punjab. *Oxford Economic Papers,* 49(4), 557-585.

Binzel, C., E. Field, and R. Pande (2013). Does the Arrival of a Formal Financial Institution Alter Informal Sharing Arrangements? Experimental Evidence from Village India. *Working paper.*

Chandrasekhar, A. G., R. M. Townsend, and J. P. Xandri (2019). Financial Centrality and the Value of Key Players. *Working paper*.

Chandrasekhar, A. G., C. Kinnan, and H. Larreguy (2018). Social networks as contract enforcement: Evidence from a lab experiment in the field. *American Economic Journal: Applied Economics,* 10(4), 43-78.

Conning J. (2001). Mixing and matching loans: credit rationing and spillover in a rural credit market in Chile. *City University of New York.*

Conning J. (2005). "Ventas Piratas": Product market competition and the changing pattern of access in a rural credit market in Chile. *City University of New York.*

Gine, X. (2011). Access to capital in rural Thailand: An estimated model of formal vs. informal credit. *Journal of Development Economics*, 96, 16-29.

Greenwood, J., and B. Jovanovic (1990). Financial Development, Growth, and the Distribution of Income. *Journal of Political Economy*, 1076-1107.

Heß, S. H., D. Jaimovich, and M. Schundeln (2018). Development Projects and Economic Networks: Lessons From Rural Gambia. *The Review of Economic Studies*, Accepted.

Hoff, K., and J. E. Stiglitz (1990). Introduction: Imperfect information and rural credit markets: Puzzles and policy perspectives. *The World Bank Economic Review*, 4(3), 235-250.

Jack, W., and T. Suri (2014). Risk Sharing and Transaction Costs: Evidence from Kenya's Mobile Money Revolution. *American Economic Review*, 104(1), 183-223.

Jackson, M. O. (2010). Social and Economic Networks, *Princeton University Press.*

Jackson, M. O., T. Barraquer, and X. Tan (2012). Social Capital and Social Quilts: Network Patterns of Favor Exchange. *The American Economic Review* 102(5), 1857-97.

Jain, S. (1999). Symbiosis vs. crowding-out: the interaction of formal and informal credit markets in developing countries. *Journal of Development Economics*, 59(2), 419-444.

Jeong, H. and R. M. Towennd (2008). Growth and inequality: Model evaluation based on an estimation-calibration strategy. *Macroeconomic dynamics*, 12, 231.

Kaboski, J. P., and R. M. Townsend (2011). A Structural Evaluation of a Large-Scale Quasi-Experimental Microfinance Initiative. *Econometrica*, 1357-1406.

Kaboski, J. P., and R. M. Townsend (2012). The Impact of Credit on Village Economies. *American Economic Journal: Applied Economics*, 4(2), 98-133.

Karaivanov, A., and R. M. Townsend (2014). Dynamic Financial Constraints: Distinguishing Mechanism Design From Exogenously Incomplete Regimes. *Econometrica*, 887-959.

Kinnan, C., and R. M. Townsend (2012). Kinship and Financial Networks, Formal Financial Access, and Risk Reduction. *American Economic Review*, 289-293.

Lagakos, D., A. M. Mobarak, and M. E. Waugh (2018). The Welfare Effects of Encouraging Rural-Urban Migration. *NBER Working Paper,* No. 24193.

Meghir, C., A. M. Mobarak, C. D. Mommaerts, and M. Morten (2019). Migration and Informal Insurance. *NBER Working Paper,* No. 26082.

Morduch, J. (1995). Income Smoothing and Consumption Smoothing. *Journal of Economic Perspectives*, 103-114.

Petersen, M. A., and R. G. Rajan (1997). Trade Credit: Theories and Evidence. *The Review of financial studies*, 10(3), 661-691.

Phelan, C., and R. M. Townsend (1991). Computing multi-period, information-constrained optima. *The Review of Economic Studies*, 58(5), 853-881.

Prescott, E. C., and R. M. Townsend (1984). Pareto optima and competitive equilibria with adverse selection and moral hazard. *Econometrica*, 52(1), 21-46.

Putnam, R. D. (2000). Bowling Alone: The Collapse and Revival of American Community. *New York: Simon and Schuster.*

Rosenzweig, M. R. (1988). Risk, Implicit Contracts and the Family in Rural Areas of Low-income Countries. *Economic Journal*, 1148-1170.

Samphantharak, K., and R. M. Townsend (2018). Risk and Return in Village Economies. *American Economic Journal: Microeconomics*, 1-40.

Sripakdevong, P., and R. M. Townsend (2019). Bridge Loans and Risk Sharing in the Village Money Market. *Working paper.*

Todd, P. E., and K. I. Wolpin (2006). Assessing the Impact of a School Subsidy Program in Mexico: Using a Social Experiment to Validate a Dynamic Behavioral Model of Child Schooling and Fertility. *American Economic Review*, 1384-1417.

Townsend, R. M. (1988). Information constrained insurance: The revelation principle extended. *Journal of Monetary Economics*, 411-450.

Townsend, R. M. (1994). Risk and Insurance in Village India. *Econometrica*, 539-591.

Townsend, R. M. (1995). Consumption Insurance: An Evaluation of Risk-Bearing Systems in Low-Income Economies. *The Journal of Economic Perspectives*, 83-102.

Townsend, R. M., and K. Ueda (2006). Financial Deepening, Inequality, and Growth: A Model-Based Quantitative Evaluation. *The Review of Economic Studies*, 251-293.

Udry, C. (1994). Risk and Insurance in a Rural Credit Market: An Empirical Investigation in Northern Nigeria. *Review of Economic Studies*, 495-526.

Vera-Cossio, D. A. (2019). Targeting Credit through Community Members. *Working Paper*.

Vuong, Q. H. (1989). Likelihood Ratio Tests for Model Selection and Non-nested Hypotheses. *Econometrica*, 57(2), 307-333.

Table 1: Variance Covariance Decomposition Analysis (Before and After the 2001 Village Fund)

	Panel A: 1999 to 2001						
		D=C+I-Q				D=C-Q	
	(1)	(2)	(3)		(4)	(5)	(6)
	1st	2nd	3rd		1st	2nd	3rd
deposit	-0.0824861	0	0.3460481	deposit	-0.2239297	0	0.1194653
ROSCA	0	0	0	ROSCA	0	0	0
lending	0	0	0	lending	0	0	0
borrowing	-0.0182476	1.49785	12.54511	borrowing	-1.692076	0.8869588	7.66296
Gift	0.0767256	4.599061	43.41077	Gift	-0.8509698	3.180128	22.88811
Cash	42.16074	78.86375	97.44578	Cash	47.69524	75.68092	98.41447
Median Diff	1.418933						
Z-stats	0.4675	P-Value	0.494				
	Panel B: 2002 to 2011						
		D=C+I-Q				D=C-Q	
	1st	2nd	3rd		1st	2nd	3rd
deposit	-0.0646792	0.0480596	2.042943	deposit	-0.2285238	0.0138236	0.9103131
ROSCA	0	0	0	ROSCA	0	0	0
lending	0	0	0	lending	0	0	0
borrowing	-0.0832301	0.5687587	4.927176	borrowing	-0.4819735	0.0329142	3.624415
Gift	3.450514	16.63977	41.65852	Gift	1.475973	9.763637	32.68346
Cash	39.51367	70.35097	91.80312	Cash	34.48471	68.08108	91.89435
Median Diff	6.876133						
Z-stats	3.3247	P-Value	0.068				
DID: Median Diff (Investment- w/o Investment) 02-11 - Median Diff (Investment- w/o Investment) 99-01							
Median DID	5.4572						
Z-stats	7.4805	P-Value	0.006				

Note: This table shows the variance-covariance decomposition on households' deficits using the Townsend Thai monthly data in 16 villages from 1999 to 2011. We restrict the sample to the poor households, with initial wealth in 1999 below the 25% quantile. Panel A is for the pre-village fund period from 1999 to 2001, and Panel B is for the post-village fund period from 2002 to 2011. In columns (1) to (3), the deficit is defined as the consumption plus investment minus the production (i.e., D=C+I-Q). In columns (4) to (6), the deficit is defined as the consumption minus the production (i.e., D=C-Q). The variation of deficit is decomposed by deposit, ROSCA, lending, borrowing, gift, and cash. Columns (1) and (4) report the value of the 25% quantile, columns (2) and (5) report the value of the median, and columns (3) and (6) report the value of the 75% quantile. We report the median differences of gifts between columns (2) and (5) in Panel A and B, respectively. We also report the difference-in-differences of the median of gifts between Panel A and B (post-village fund vs. pre-village fund), with the z-stats and P-value for this DID.

Table 2: Variance Covariance Decomposition Analysis (Kinship)

Panel A: 1999 to 2001							
	KIN				No KIN		
	(1)	(2)	(3)		(4)	(5)	(6)
	1st	2nd	3rd		1st	2nd	3rd
deposit	-0.0831796	0	0.3460481	deposit	-0.0824861	0	1.304691
ROSCA	0	0	0	ROSCA	0	0	0
lending	0	0	0	lending	0	0	0
borrowing	-0.0379124	1.970992	14.62181	borrowing	0	0	3.368362
Gift	0.0564407	4.062475	43.26854	Gift	0.7870868	20.05442	51.18238
Cash	36.09503	78.83343	97.44578	Cash	46.2137	79.0435	98.44392
Median Diff	-15.991945						
Z-stats	0.9606	P-Value	0.327				
Panel B: 2002 to 2011							
	KIN				No KIN		
	1st	2nd	3rd		1st	2nd	3rd
deposit	-0.0564173	0.0646212	2.042943	deposit	-0.5837829	-0.0006449	5.861598
ROSCA	0	0	0	ROSCA	0	0	0
lending	0	0	0.0030578	lending	0	0	0
borrowing	-0.1298965	0.5950256	5.57686	borrowing	-0.0159046	0.0814541	2.943943
Gift	3.998044	18.13391	46.26608	Gift	0.6962006	6.380914	28.66442
Cash	34.27515	69.53503	90.47472	Cash	46.30897	89.84628	98.03957
Median Diff	11.752996						
Z-stats	2.9419	P-Value	0.086				
	DID: Median Diff (Kin-non-Kin) in 02-11 - Median Diff (Kin-non-Kin) in 99-01						
Median DID	27.744941						
Z-stats	2.12	P-Value	0.035				

Note: This table shows the variance-covariance decomposition on households' deficits using the Townsend Thai monthly data in 16 villages from 1999 to 2011. The sample is restricted to the poor households, with initial wealth in 1999 below the 25% quantile. Panel A is for the pre-village fund period from 1999 to 2001, and Panel B is for the post-village fund period from 2002 to 2011. The deficit is defined as the consumption plus investment minus the production (i.e., D=C+I-Q). In columns (1) to (3), we restrict to the households with kinship, and In columns (4) to (6), we restrict to the households without kinship. The variation of deficit is decomposed by deposit, ROSCA, lending, borrowing, gift, and cash. Columns (1) and (4) report the value of the 25% quantile, columns (2) and (5) report the value of the median, and columns (3) and (6) report the value of the 75% quantile. We also report the difference-in-differences of the median of gifts between Panel A and B (post-village fund vs. pre-village fund), with the z-stats and P-value for this DID.

Table 3: Comparison among four financial regimes on the poorest 25% households

			Panel A: 1999 to 2001				
	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	κ	MLE
MH	0.1952	0.3123	4.9461	0.5041	0.0100		-6.5126
S*	0.1204	1.2295	2.0000	0.0005	0.6020		-6.3185
LB*	0.1203	1.3862	2.0376	0.0019	0.6377		-6.3223
CSV	0.298652	2.860451	0.057812	0.80014	0	0.31532	-7.5245
Vuong test	CSV vs. B	Z-Stats	Prob				
		16.608	0.000				
			Panel B: 2002 to 2011				
	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	κ	MLE
MH	0.2532	0.0145	0.5967	0.3484	0.0463		-6.7557
S	0.1543	1.0757	2.1138	0.0280	0.9983		-6.4317
LB	0.1539	1.2607	2.1716	0.0002	0.9995		-6.4117
CSV*	0.104324	0.147309	0.122625	0.152894	0.141101	0.172141	-6.2859
Vuong test	CSV vs. B	Z-Stats	Prob				
		-4.8564	0.000				

Note: This table shows the maximum-likelihood estimations (MLE) of four financial regimes: a dynamic state verification regime with capital and risk aversion (CSV) , moral hazard regime with unobserved effort (MH), and exogenously incomplete regimes: saving only (S) and lending/borrowing (LB). We use the data on households' consumption, production, investment, and capital from Townsend Thai monthly data from 1999 to 2011. We restrict the sample to the households with initial wealth in 1999 below the 25% quantile. For MH, S, and LB regimes, we estimate five parameters (e.g., γ_{me}, σ, θ, μ_{ω}, and γ_{ω}). For CSV regime, we estimate an additional parameter κ that measures the verification cost. We employ the Voung test to statistically compare the four regimes, and * denotes the regimes that statistically fit the best in MLE (i.e., dominate regime). Panel A is for the pre-village fund period from 1999 to 2001. Panel B is for the post-village fund period from 2002 to 2011.

Table 4: Informal Kinship Networks and Verification Costs

Panel A: 1999 to 2001							
	κ	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	MLE
KIN 0 (no relatives)	0.014080	0.225946	0.0039715	0.273718	0.796307	0.023710	7.8443
S.E.	0.002150	0.002574	0.001128	0.003632	0.007326	0.010400	
KIN 1-10	0.004353	0.121607	0.0421057	0.140673	0.290268	0.227749	5.9729
S.E.	0.000369	0.000166	8.363E-05	3.88E-05	0.000423	0.000418	
K (Kin 0 - Kin 1-10)	Diff	SE	T-stats				
	0.009727	0.002177	4.4690499				
Panel B: 2002 to 2011							
	κ	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	MLE
KIN 0 (no relatives)	0.336663	0.296589	0.114849	0.159671	0.338498	0.047381	7.9868
S.E.	0.003658	0.01096	0.0004186	0.003255	0.028069	0.017703	
KIN 1-10	0.014003	0.198384	0.0111501	0.192743	0.229734	0.098548	6.4459
S.E.	0.041371	0.036364	0.044039	0.021714	0.036892	0.033547	
K (Kin 0 - Kin 1-10)	Diff	SE	T-stats				
	0.32266	0.005362	60.176432				
DID: Mean Diff (Kin 0 - Kin 1-10) in 02-11 - Mean Diff (Kin 0 - Kin 1-10) in 99-01							
Mean DID	0.312933						
T-stats	48.58	P-Value	0.00				

Note: This table shows the comparisons of verification costs (i.e., κ) in the CSV model between the households with kinships vs. the households without kinships. We use the data on households' consumption, production, investment, and capital from Townsend Thai monthly data from 1999 to 2011. We restrict the sample to the households with initial wealth in 1999 below the 25% quantile. Panel A is for the pre-village fund period from 1999 to 2001. Panel B is for the post-village fund period from 2002 to 2011. To calculate the standard errors of estimated parameters in the CSV model, we employ the bootstraps by randomly selecting the data for consumption, investment, production, and capitals repeatedly and estimate the κ, γ_{me}, σ, θ, μ_{ω}, and γ_{ω} for each draw. We report the t-test of κ between the households with kinships vs. the households without kinships from 2002 to 2011 in Panel A and B, respectively. We also report the difference-in-differences of κ between Panel A and B (post-village fund vs. pre-village fund), with the T-stats and P-value for this DID.

Table 5: Informal Kinship Networks to Village Fund Borrowers and Verification Costs

			Panel A: 1999 to 2001				
	κ	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	MLE
HH with No Kin to Village Fund Borrowers	0.0106	0.2736	0.0025	0.2206	0.8207	0.0071	8.3660
SE	3.6448E-05	0.00079569	4.2602E-06	0.00409522	0.01241136	0.00097369	
HH with Kin to Village Fund Borrowers	0.1646	0.2054	0.0936	0.1634	0.2000	0.0106	6.3403
SE	0.00052602	3.9617E-05	7.7311E-18	4.3645E-05	0.00305526	0.00181586	
K (HH with no Kin - HH with Kin)	Diff	SE	T-stats				
	-0.154016	0.0003706	-415.58562				
			Panel B: 2002 to 2011				
	κ	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	MLE
HH with No Kin to Village Fund Borrowers	0.7329	0.2456	0.0091	0.2092	0.0436	0.0999	7.5288
SE	0.0020044	0.0037848	0.0002804	0.000054	0.0220414	0.0426913	
HH with Kin to Village Fund Borrowers	0.0729	0.1222	0.0599	0.1493	0.1860	0.1554	6.0314
SE	0.0004576	0.0001817	0.0002322	6.97E-06	0.0049371	0.0083519	
K (HH with no Kin - HH with Kin)	Diff	SE	T-stats				
	0.659971	0.0002654	2486.70386				
DID: Mean Diff (HH with no Kin - HH with Kin) in 02-11 - Mean Diff (HH with no Kin - HH with Kin) in 99-01							
Mean DID	0.813987						
T-stats	1795.28	P-Value	0.00				

Note: This table shows the comparisons of verification costs (i.e., κ) in the CSV model between the households with kinship connections to the village borrowers vs. the households without such connections. We use the data on households' consumption, production, investment, and capital from Townsend Thai monthly data from 1999 to 2011. We restrict the sample to the households with initial wealth in 1999 below the 25% quantile. Panel A is for the pre-village fund period from 1999 to 2001. Panel B is for the post-village fund period from 2002 to 2011. To calculate the standard errors of estimated parameters in the CSV model, we employ the bootstraps by randomly selecting the data for consumption, investment, production, and capitals repeatedly and estimate the κ, γ_{me}, σ, θ, μ_{ω}, and γ_{ω} for each draw. We report the t-test of κ between the households with kinship connections to the village fund borrowers vs. the households without such connections in Panel A and B, respectively. We also report the difference-in-differences of κ between Panel A and B (post-village fund vs. pre-village fund), with the t-stats and P-value for this DID.

Table 6: Verification Costs in Small and Large Villages

	Panel A: 1997 to 2001						
	κ	γ_{me}	σ	θ	μ_ω	γ_ω	MLE
Small Village	0.282826153	0.268118733	0.107049883	0.168945253	0.754306449	0.262139513	-8.082180652
SE	0.008022608	0.001639284	9.91E-18	3.97E-18	0.008164764	0.019944727	
Large Village	0.058982018	0.23509104	0.04163214	0.235574299	0.834302362	0.235520325	-8.193408723
SE	0.001729031	0.0003304	0.0000067	0.0000030	0.0009124	0.0017534	
K (Small-Large)	Diff	SE	T-stats				
	0.223844	0.0075724	29.56052705				
	Panel B: 2002 to 2007						
	κ	γ_{me}	σ	θ	μ_ω	γ_ω	MLE
Small Village	0.150167734	0.267625168	0.349630243	0.083958243	0.697924565	0.228167075	-6.4747
SE	0.002505662	0.002343952	3.65E-05	8.11E-05	0.006334235	0.009896955	
Large Village	0.276450131	0.250982775	0.282895191	0.096496325	0.502259598	0.007773151	-6.533
SE	0.0000871	0.0000125	0.0003348	0.0000677	0.0238033	0.0013186	
K (Small-Large)	Diff	SE	T-stats				
	-0.126282397	0.0003237	-390.1217093				
	DID: Mean Diff (Small-Large) in 02-07 - Mean Diff (Small-Large) in 97-01						
Mean DID	-0.350127						
T-stats	-30.98	P-Value	0.00				

Note: This table shows the comparisons of verification costs (i.e., κ) in the CSV model between the households in small vs. large villages. We use the data on households' consumption, production, investment, and capital from Townsend Thai annual data in 64 villages from 1997 to 2007. We restrict the sample to the households with initial wealth in 1997 below the 25% quantile. Panel A is for the entire sample period from 1997 to 2001. Panel B is for the pre-village fund period from 1997 to 2007. To calculate the standard errors of estimated parameters in the CSV model, we employ the bootstraps by randomly selecting the data for consumption, investment, production, and capitals repeatedly and estimate the κ, γ_{me}, σ, θ, μ_ω, and γ_ω for each draw. We report the t-test of κ between the households in small vs. large villages in Panel B and C, respectively. We also report the difference-in-differences of κ between Panel B and C (post-village fund vs. pre-village fund), with the t-stats and P-value for this DID.

Table 7: Financial Regime Shift for High TFP Households

	Panel A: 1997 to 2001						
	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	κ	MLE
MH	0.419538162	0.016454	1.045769	0.861156	0.038206		-9.83814
S	0.415372405	0	2	0.064312	0		-9.82455
LB*	0.42962344	0	1.042272	0.019584	0.019107		-9.80088
CSV	0.460832422	0.002511	0.140387	0.980704	0.007575	0.01009	-9.80583
	Panel B: 2002 to 2007						
	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	κ	MLE
MH	0.631354874	0.008426	0.525121	0.832958	0.036906		-10.5607
S	0.578385219	0.203531	0.1	0.292281	0.000815		-10.6567
LB	0.566821649	0	0.77	0.064312	0.001806		-10.6097
CSV*	0.635813722	0	0.236366	0.8	0	0.010349	-10.5195

Note: This table shows the maximum-likelihood estimations (MLE) of four financial regimes: a dynamic state verification regime with capital and risk aversion (CSV) , moral hazard regime with unobserved effort (MH), and exogenously incomplete regimes: saving only (S) and lending/borrowing (LB). We use the data on households' consumption, production, investment, and capital from Townsend Thai annual data from 1997 to 2007. We restrict the sample to the households with initial TFP in 1997 above the median. For MH, S, and LB regimes, we estimate five parameters (e.g., γ_{me}, σ, θ, μ_{ω}, and γ_{ω}). For CSV regime, we estimate an additional parameter κ that measures the verification cost. Panel A is for the pre-village fund period from 1997 to 2001. Panel B is for the post-village fund period from 2002 to 2007.

Online Appendix for

Enhanced Informal Networks: Costly State Verification and Village Fund Intervention

Table A1: Comparison among four financial regimes on the richest 25% households

	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	κ	MLE
Panel A: 1999 to 2001							
MH	0.0507	0.8545	3.4440	0.3967	0.0409		-3.45674
S	0.0664	0.3071	2.9475	0.8724	0.0194		-3.5184
LB*	0.0652	0.3775	2.1093	0.9576	0.0192		-3.25745
CSV	0.087635	2.205649	0.305572	0.464558	0.022001	0.3	-3.7511
Panel B: 2002 to 2011							
	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	κ	MLE
MH	0.0743	1.0136	3.2833	0.6454	0.0430		-4.11509
S	0.0797	0.5000	2.8754	0.9364	0.0011		-4.01269
LB*	0.0757	2.9956	2.6261	0.9978	0.0160		-3.7946
CSV	0.112561	2.433587	4.117231	0.509899	0	0.01	-5.1688

Note: This table shows the maximum-likelihood estimations (MLE) of four financial regimes: a dynamic state verification regime with capital and risk aversion (CSV) , moral hazard regime with unobserved effort (MH), and exogenously incomplete regimes: saving only (S) and lending/borrowing (LB). We use the data on households' consumption, production, investment, and capital from Townsend Thai monthly data from 1999 to 2011. We restrict the sample to the rich households, with initial wealth in 1999 above the 75% quantile. For MH, S, and LB regimes, we estimate five parameters (e.g., γ_{me}, σ, θ, μ_{ω}, and γ_{ω}). For CSV regime, we estimate an additional parameter κ that measures the verification cost. We employ the Vuong test to statistically compare the four regimes, and * denotes the regimes that statistically fit the best in MLE (i.e., dominate regime). Panel A is for the pre-village fund period from 1999 to 2001. Panel B is for the post-village fund period from 2002 to 2011.

Table A2: Variance Covariance Decomposition Analysis from 1999 to 2011

Panel A: Richest 25% households

	D=C+I-Y				D=C-Y		
	(1)	(2)	(3)		(4)	(5)	(6)
	1st	2nd	3rd		1st	2nd	3rd
deposit	-0.0110956	0.8811659	12.68284	deposit	-0.1545141	0.5316959	5.462239
ROSCA	0	0	0	ROSCA	0	0	0
lending	0	0	0.0043046	lending	0	0	0.0027251
borrowing	0	1.227418	12.48462	borrowing	-0.5264556	0.7519735	10.3852
Gift	1.227739	5.867592	28.68589	Gift	0.219123	3.325574	17.2347
Cash	32.40092	66.69633	86.12543	Cash	36.83528	70.53376	89.67932
Median Diff	2.542018						
Z-stats	2.9412	P-Value	0.086				

Panel B: Poorest 25% households

	D=C+I-Y				D=C-Y		
	1st	2nd	3rd		1st	2nd	3rd
deposit	-0.059039	0.058865	1.83884	deposit	-0.271496	0.00958	0.815835
ROSCA	0	0	0	ROSCA	0	0	0
lending	0	0	0.007148	lending	0	0	0.003053
borrowing	0	1.04757	5.86912	borrowing	-0.847523	0.054241	4.34595
Gift	4.12008	17.7979	40.1114	Gift	1.95387	9.54806	30.7719
Cash	39.8131	67.5713	91.8527	Cash	43.2032	66.6337	91.2177
Median Diff	8.24984						
Z-stats	6.2857	P-Value	0.012				

DID: Median Diff (Investment- w/o Investment) for poor - Median Diff (Investment- w/o Investment) for rich

Median DID	5.707822		
Z-stats	1.51	P-Value	0.131

Note: This table shows the variance-covariance decomposition on households' deficits using the Townsend Thai monthly data in 16 villages from 1999 to 2011. Panel A restricts the sample to the rich households, with initial wealth in 1999 above the 75% quantile, and Panel B restricts the sample to the poor households, with initial wealth in 1999 below the 25% quantile. In columns (1) to (3), the deficit is defined as the consumption plus investment minus the production (i.e., D=C+I-Y). In columns (4) to (6), the deficit is defined as the consumption minus the production (i.e., D=C-Y). The variation of deficit is decomposed by deposit, ROSCA, lending, borrowing, gift, and cash. Columns (1) and (4) report the value of the 25% quantile, columns (2) and (5) report the value of the median, and columns (3) and (6) report the value of the 75% quantile. We report the median differences of gifts between column (2) and (5) in Panel A and B, respectively. We also report the difference-in-differences of the median of gifts between Panel A and B (poor vs. rich), with the z-stats and P-value for this DID.

Table A3: Informal Kinship Networks and Verification Costs (1999 to 2011)

	κ	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	MLE
Panel A: Kinship Network							
KIN 0 (no relatives)	0.20368869	0.2995335	0.06051521	0.14280715	0.56795583	0.01524593	8.4573
S.E.	7.85E-07	1.22E-06	7.23E-18	2.17E-17	2.43E-03	1.79E-04	
KIN 1-10	0.01571187	0.19868542	0.01225892	0.19139811	0.24676946	0.09443732	6.4108
S.E.	0.00032838	0.00021463	6.3759E-05	5.0044E-05	0.00079473	0.0004139	
Panel B: Kinship to the VF Borrower	κ	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	MLE
HH with No Kin to Village Fund Borrowers	0.1691	0.2581	0.0899	0.1731	0.5342	0.0127	7.1612
	2.96E-06	0.0004161	0	0.000014	0.0491638	0.0142236	
HH with Kin to Village Fund Borrowers	0.0102	0.1978	0.0102	0.1937	0.1812	0.0434	6.4047
	0.00148496	0.00122152	0.00166782	0.00082503	0.00110002	0.00154149	

Note: This table shows the comparisons of verification costs (i.e., κ) in the CSV model between the households with and without kinship. We use the data on households' consumption, production, investment, and capital from Townsend Thai monthly data from 1999 to 2011. We restrict the sample to the households with initial wealth in 1999 below the 25% quantile. Panel A compares the households with connections in the kinship network vs. the ones without such connections. Panel B compares the households with kinship connections to the village fund borrowers vs. the ones without such connections. To calculate the standard errors of estimated parameters in the CSV model, we employ the bootstraps by randomly selecting the data for consumption, investment, production, and capitals repeatedly and estimate the κ, γ_{me}, σ, θ, μ_{ω}, and γ_{ω} for each draw.

Table A4: Simulated Data Test

True parameters	γ_{me}	σ	θ	μ_ω	γ_ω	κ	
	0.234	0.212	0.113	0.311	0.0193	0.912	
	γ_{me}	σ	θ	μ_ω	γ_ω	κ	MLE
MH	0.2122	0.6811	2.1594	0.9741	0.9960		-5.8598
S	0.2727	0.0000	0.1042	0.0203	0.0083		-6.1491
B	0.2867	0.0000	3.9045	0.0607	0.0898		-6.1914
CSV*	0.2130	0.0000	0.0986	0.5603	0.0572	0.9473	-5.7555

Note: This table shows the maximum-likelihood estimations (MLE) of four financial regimes: a dynamic state verification regime with capital and risk aversion (CSV) , moral hazard regime with unobserved effort (MH), and exogenously incomplete regimes: saving only (S) and borrowing (B) by using simulated data. We employ the dynamic CSV model and the pre-selected parameters (i.e., true parameter) to generate the data of households' consumption, production, investment, and capital. Based on the simulated data, we employ the Voung test to statisically compare the four regimes, and * denotes the regimes that statistically fit the best in MLE (i.e., dominate regime).

Table A5: Comparison among four financial regimes on whole sample households

			1999 to 2011				
	γ_{me}	σ	θ	μ_{ω}	γ_{ω}	κ	MLE
MH	0.2092	0.4012	3.8762	0.6107	0.0100		-5.7463
S	0.1702	1.2759	0.6809	0.8511	0.0100		-5.3814
LB*	0.1543	2.1477	4.7575	0.6489	0.0100		-5.2530
CSV	0.1647	0.2550	0.0222	0.1175	0.1222	0.9572	-5.7104
Vuong test	CSV vs. LB	Z-Stats	Prob				
		9.5198	0.0000				

Note: This table shows the maximum-likelihood estimations (MLE) of four financial regimes: a dynamic state verification regime with capital and risk aversion (CSV), moral hazard regime with unobserved effort (MH), and exogenously incomplete regimes: saving only (S) and lending/borrowing (LB). We use the data on households' consumption, production, investment, and capital from Townsend Thai monthly data with 616 households in 16 villages from 1999 to 2011. For MH, S, and B regimes, we estimate five parameters (e.g., γ_{me}, σ, θ, μ_{ω}, and γ_{ω}). For CSV regime, we estimate an additional parameter κ that measures the verification cost. We employ the Vuong test to statistically compare the four regimes, and * denotes the regimes that statistically fit the best in MLE (i.e., dominate regime).