Self-Control or Social Control? Peer Effects on Temptation Consumption*

December 4, 2018

Abstract

This paper examines peer effects on self-control problems. I construct a theoretical model to describe how peer networks influence consumption behaviors through social norms. Using monthly survey data conducted in 16 Thai villages from 1999 through 2004, I found that peer's temptation consumption significantly impact individuals' temptation consumption such as alcohol, tobacco, and gambling. One baht increase in peer's temptation consumption leads to 1.5 increase in own temptation consumption. With the detailed household-level social network information defined by the actual transactions, this paper identifies peer effects using a friend of a friend (excluded network) as the instrument. The panel nature of this instrument overcomes various common identification challenges, such as reflection, correlated effects, and common unobservable shocks, in the literature. My findings suggest that these peer effects are driven primarily by social norms, rather than risk sharing.

*I am grateful to Jennifer Alix-Garcia, Laura Schechter, Jean-Paul Chavas, Steven N. Durlauf, John Chung-En Liu and seminar participants at MIEDC and UW-Madison for their helpful comments. I am also thankful to Robert Townsend and the staff of the Townsend Thai Project for the generous data access and support. This project has received funding support from the Vilas Research Travel Award at the University of Wisconsin-Madison.

1 Introduction

Current literature in development economics points out that behavioral constriants can reinforce poverty (Banerjee and Mullainathan, 2010; Becker and Mulligan, 1997; Bernheim et al., 2015; Chemin et al., 2013; Haushofer, 2011; Haushofer et al., 2011; Haushofer and Fehr, 2014; Laajaj, 2017; Mani et al., 2013). One central challenge for the poor is the so-called self-control problems–people are tempted to do things that provide immediate satisfaction, rather than sacrificing now for the future. For example, in terms of finance, individuals may overborrow when they do not recognize their preferences for immediate payoffs (Heidhues and Kőszegi, 2010). Crop farmers may have difficulty saving small amounts of money upfront for fertilizers to be used later, resuling in failures to maximize yields (Banerjee and Duflo, 2007). Poor households also spend a considerable amount of disposable income on entertainment and temptation goods such as alcohol and tobacco.[1] In particular, alcohol consumption can further reduce cognitive capacity and lead to less savings (Schilbach, 2015). Such behaviors are of utmost interest to policymakers, especially in light of the promotion of financial tools to the poor.

On the other hand, social influence plays a critical part in the communities studied by development economists. Poor households rely on social networks to share financial risks and information.[2] For example, farmers' technology adoption behaviors are affected by other farmers in their networks (Conley and Udry, 2010; Foster and Rosenzweig, 1995; Maertens, 2017; Moser and Barrett, 2006). Peer effects are important determinants in financial behaviors, such as microfinance/insurance take-up (Banerjee et al., 2013; Cai and Song, 2013), loan repayment (Breza, 2011), gift-giving (Chen et al., 2011), and asset purchasing (Bursztyn et al., 2013).

Against this background, this paper conceptualizes self-control problems not merely an individual's problem. I incorporate peer effects into our understanding of the myopic behaviors of the poor, especially focus on the temptation consumption. The main research questions I address are: (1) Are households' temptation consumption affected by their peers' temptation consumption? (2) If so, what is the mechanism underlying this relationship?

I begin by including peer effects into the temptation model developed by Banerjee and

[1] In this project, I find that yearly temptation consumption is equivalent to households' average yearly spending on education. Evans and Popova (2017) discuss the concerns surrounded with temptation consumption and provide various empirical evidence regarding this type of consumption, particularly focusing on the effect of cash transfers.

[2] Many aspects of the poor's life can be affected by their networks. See the more comprehensive review paper focusing on networks in developing countries by Chuang and Schechter (2015)

Mullainathan (2010). I define temptation goods as alcohol, tobacco, and gambling, because these goods can further inform the potential negative consequences of the self-control problems.[3] Temptation consumption, which is one embodiment of the self-control problem, may further perpetuate poverty. The peer effect that I incorporate into the model is derived from the idea that people want to follow social norms and thus suffer disutility when deviating from their peers' behaviors. My model predicts that peers have an impact on temptation consumption, especially among observable goods. My model also demonstrates that in the event of a shock at either the household or network level, poor households will consume proportionately more temptation goods than non-temptation goods. Both of these predictions have important implications for a larger range of phenomena, from saving and investment behaviors to the poverty trap.

To examine spending behaviors empirically, I use data from the Thai Townsend Monthly Project from 1999 to 2004. This dataset includes extensive information about household-level consumption and social relationships. I construct social network linkage information for each household using real-world transactions (e.g., borrowing, lending, gift-giving, and labor sharing described in the survey). The extensive network information available in my data helps circumvent several common identification challenges in the social network literature.

There are many concerns in identifying peer effects. For example, the reflection problem refers to the inability to separate the influence of peer groups' behaviors from the exogenous characteristics of the groups (Manski, 1993). Another identification challenge is to the unobservable correlated shocks and omitted covariates. For example, households in the same village or join the same organization may suffer from the same unobservable shocks that drive their consumption behaviors. Lastly, people select their own peers, so making the network definition endogenous.

To address the identification challenges, I apply an instrumental variable approach to identify peer effects using lagged consumption data from an excluded network—friends' of friends who are not linked directly with the focal individual. This idea has been developed as effective in many other contexts to identify peer effects (Bramoullé et al., 2009; Helmers and Patnam, 2014; Lee, 2007; Nicoletti et al., 2018; Quintana-Domeque and Wohlfart, 2016).[4] The exclusion restriction assumption relies on the fact that excluded peers do not directly

[3]Based on Banerjee and Duflo (2007), alcohol and tobacco are the top items most households wanted to cut back in the expenditure survey in India. Based on my anecdotal fieldwork, those items are an appropriate definition for temptation goods in the context of Thailand.

[4]Bramoullé et al. (2009); Lee (2007) both provide proof using intransitive triad (degree-two friend) to serve for identification.

interact with the focal individuals—there is no actual labor-sharing, gift-giving, and financial transaction relations during the whole 72-month survey period. Another benefit of my approach is that the instrumental variable is time-varying, and thus any time-invariant covariates can be controlled for through household, village-year, and seasonal fixed effects. This large set of fixed effects helps eliminate the correlated effects and unobservable common shocks. The lagged consumption variables prevent the problem of reverse causation or a joint consumption decision.

Overall, I find that households' temptation consumption, especially the consumption of more observable goods, is subject to strong peer effects. In particular, I find that one bhat increase in peers' average temptation consumption leads to 1.5 bhat increase in individual's temptation consumption. The results also indicate that poor households consume a higher share of temptation goods of their marginal dollar than rich households—temptation consumption has a concave shape. This finding confirms the theoretical assertion that poor households are subject to greater cognitive constraints (Chemin et al., 2013; Mani et al., 2013). Further robustness tests reveal that temptation consumption decisions are guided by social norms, rather than risk-sharing. In sum, the results indicate that peer effects exacerbate myopic consumption behaviors and suggest that peer behavior is an important element in modeling consumption decisions of the poor.

My study contributes to the current literature in several ways. First, I enrich the behavioral economics literature by incorporating peer effects into models of self-control problems. This paper intends to empirically examine the social element in the self-control theory using relatively long-term high-frequency consumption data.[5] Battaglini et al. (2005) is the only theoretical paper that models peers' influence on individuals' self-control problem.[6] There are few empirical studies directly test peer effects on self-control, and all of them focus on the student population in a developed country. For example, Battaglini et al. (2017) use data from the National Longitudinal Survey of Adolescent to Adult Health (Add Health) to understand high students' self-control level in peer groups. Limited by the data, they use one hypothetical question - Do you usually go with your "gut feeling?" - to measure students' self-control. Similar to Battaglini et al. (2017), Buechel et al. (2014) relies on laboratory experiments and find that students who are more connected have more self-control. The

[5]There are studies on peer effects on consumption, but mostly using administrative yearly data. As consumption data is very noisy, the unique high-frequency data collection process at monthly (and many food categories at weekly basis) basis allows us to credibly analyze temptation consumption.

[6]Their model shows that individuals' self-control problems can be either worsened or improved by the peer effect depending on the type of person: people who have sufficient level of self-control - strong type - can positively benefit from interacting with their peers.

current empirical literature are based on the key assumption in Battaglini et al. (2005) that agents' types (high or low self-control) are correlated so that peers' actions are informative and can endogenously affect agents' decisions to be in a social group or not. This assumption may not be appropriate in my context. In rural Thailand, peers may not be correlated in terms of their self-control types. Villagers interact with peers in farming activities and various social and religious events. This paper takes a different approach without imposing this assumption to provide theoretical intuition and empirical evidence based on a relatively long-term monthly consumption data on this matter.

Second, this paper adds to the literature on consumption externalities, which is mostly conducted in developed countries. One strand of the literature focuses on adolescents' risk taking behaviors, such as smoking and alcohol usage (Alexander et al., 2001; Card and Giuliano, 2013; Duncan et al., 2005; Gaviria and Raphael, 2001; Krauth, 2005; Kremer and Levy, 2008; McVicar, 2012; Nakajima, 2007). Another strand of literature is to identify the general social influence on consumption behaviors using administrative boundaries to define the reference group. However, this strand of literature does not directly survey people's social circles. For example, Charles et al. (2009) use the same racial group as the reference group definition in the United States and find that consumption is a way for status seeking[7]. Others also find a social influence on households' consumption choice based on different reference group definition such as, postcodes in Netherlands (Kuhn et al., 2011), county in UK (Quintana-Domeque and Wohlfart, 2016), and city in the U.S. (Ravina, 2005). Giacomo De Giorgi (2017)'s paper uses the so-called distance-3 peer—my co-workers' spouses' co-workers—to instrument peer effects on household consumption from Danish's tax record data. My scope of analysis is to understand a more general population in a developing country, which may yield guidance on poverty reduction policies. As people do not form social ties simply based on geographic or racial boundaries, my network data is advantageous to capture social relations beyond the natural physical boundaries using long-term real-world transactions.

Third, this paper speaks to the literature on psychology and poverty. There is emerging research showing that poverty reduces cognitive resources and thus induces disadvantageous economic behaviors (Chemin et al., 2013; Haushofer, 2011; Haushofer et al., 2011; Haushofer and Fehr, 2014; Mani et al., 2013). For example, Chemin et al. (2013) find that rain deficits increase cortisol levels among farmers, especially those who are highly dependent on agri-

[7]There are also other papers using demographic dimensions as the assumption of reference group (Alessie and Kapteyn, 1991; Lewbel et al., 2016; Maurer and Meier, 2008)

culture. Mani et al. (2013) also find shocking evidence that poor farmers' cognitive function decreases before the harvest cycle, as compared with the same farmers after the harvest, when they are rich. This is because poor farmers' mental resources are preoccupied with poverty-related concerns. Similar indications can be found in Shah et al. (2012), who show, through different experiments, that scarcity can consume mental resources. In this paper, I also find that in the face of negative income shocks, poor households' temptation consumption behaviors, which may be driven by their cognitive distress, are also more severe.

Finally, within the policy discussion, my results deepen the understanding of consumption behaviors among the poor and suggest policy applications for future financial instruments. Recent financial tools in the microfinance industry attempt to address the self-control problem. One example is a "commitment saving device," which has been shown to help myopic people to save more (Ashraf et al., 2006). Another example is the establishment of local saving groups (e.g., self-help group[8] in India), which utilize a collective mechanism to overcome individual-level self-control limitations (Gugerty, 2007). The evidence in this paper suggests the need for caution when relying on peer effects to overcome moral hazard issues, because these effects may entail unintended consequences. Socializing with myopic peers can lead an individual to allocate his financial resources more myopically.

2 Social Norm Model

This section presents individuals' consumption behaviors modified by a social norm model. In my model, individuals suffer from disutility when their temptation consumption deviates from the average peers' behavior. The model yields several predictions. First, an individual's temptation consumption is positively related to his peers'. Second, the observability of the goods matters in the social norm model. In addition, individuals' temptation consumption still comoves with their peers', even controlling for the total consumption of peers. Lastly, in the event of negative shocks, peers have positive effects on individuals' consumption.

[8]Self-help group (SHG) is an instrument employed to help villagers to save. The practice, originally promoted by local non-governmental organizations in India, has an anti-poverty agenda. SHGs usually comprise 10-20 people, and are mostly for women. Members make regular contributions to the group savings. When a group accumulates sufficient capital, members can borrow from the fund. SHGs aim to improve the financial situations of poor women and increase their economic mobility, especially in locations where formal financial institutions have little market penetration.

2.1 Household Maximization Problem

I assume no information asymmetry within the network among different consumption goods because people in the same social network group have very close financial and social relationships. This assumption can be relaxed later by varying the observability of the goods.

The basic setup follows the model created by Banerjee and Mullainathan (2010). This model provides insights for understanding self-control problems through goods-specific preferences, and it yields similar predictions to a hyperbolic discounting model. Household i maximizes a utility function that depends on two kinds of separable consumption—temptation goods (z_i) and goods without temptation (x_i). Temptations are consumption urges. For example, alcohol and tobacco are the type of goods that the present self would gain utility by consuming them, but do not gain utility from thinking about future self's consumption in them. This feature yields good-specific impatient behaviors biased toward the present since any temptation consumption left for the future would be viewed as a waste from the present self's point of view. This assumption is supported by Schilbach (2015)'s randomized control experiment in India, in which he offers incentives for sobriety and found that low-income groups exhibit a high demand for commitment to increase their sobriety.

This model also assumes a concave temptation function $z(.)$, which is reasonable as there seems to be a concave trend of temptation consumption from figure 3 that temptation increases with consumption at a decreasing rate. This assumption implies different levels of myopia for the rich and the poor[9]—the poor behave as if they were more myopic than the rich. This set-up allows us to capture the fact that the poor may discount their lives very differently from the rich because of the larger uncertainty in life.

To simplify the maximization problem, household i lives for only two periods. There are no savings in the last period. The period 1 self maximizes $u(x_1) + v(z_1) + \delta u(x_2)$, where δ is the discount factor. The period 1 self gains utility from both goods consuming in the first period, but gets discounted utility from x goods consuming only in the second period. This setup fits the property of the temptation goods, which households cannot resist "now," but

[9] I did not use the standard hyperbolic discounting model, or Battaglini et al.'s (2005) self-control model, because I do not have the direct behavioral variables to conduct relevant empirical tests derived from these models. In Battaglini et al.'s (2005) model, they separate people into different types—people with a strong will who are less subject to self-control and people with weak willpower who more easily have self-control problems. They derive equilibrium group behavior by incorporating peer interactions into the model. This model is theoretically useful and related to my research question, but there is not enough information in these data to conduct empirical tests based on this model. At the same time, based on my fieldwork experience, the temptation framework is more reflective of the reality, which can also be viewed as an extreme version of hyperbolic preferences over temptation goods.

do not value the future self to consume. The temptation goods generate utility only at the point of consumption. There is a disagreement of the composition of consumption between the current self and the future self. From period 1 self's point of view, any money left for temptation spending in the second period would be a waste.

Apart from utility gaining from consumption, people also care about how they appear within a group. People worry about behaving differently than the majority. In other words, people gain "social rewards" by conforming with others. This conforming behavior is examined within the social group that people belong to. Thus, I use the deviation function, denoted as $\Phi(.)$, to capture the deviating payoff from the group behavior. The behavior of the majority can be viewed as a "social norm." The idea is similar to the literature modeling consumption externalities, which makes own consumption dependent upon reference group's consumption (Alvarez-Cuadrado et al., 2016; Drechsel-Grau and Schmid, 2014; Maurer and Meier, 2008; Quintana-Domeque and Wohlfart, 2016). However, I take a different approach to focus on peer effects on temptation consumption.[10]

Therefore, household i in a social network group g has the following maximization problem:

$$\max_{x_{1i}, z_{1i}} u(x_{1i}) + v(z_{1i}) + \chi[\Phi(z_{1i}, \overline{z_{1-ig}})] + \delta u(x_{2i}(c_{2i})) \tag{1}$$

$$\text{s.t. } A_{2i} = (1+r)(\theta_{1i} y_{1i} - x_{1i} - z_{1i})$$

where $u'()$ and $v'() > 0$; $u''()$ and $v''() < 0$. At the same time, $v''()$ is assumed to be smaller than $u''()$. Both goods have a concave shape, but temptation goods have a more concave shape than non-temptation goods. It means that, as income/consumption increase, the marginal utility from temptation goods decreases much faster for temptation goods than non-temptation goods. This assertion indicates that the proportional spending on temptation goods over total spending should decrease as the total consumption increases. Temptation goods give people large marginal utility for the first few units (say, drinking sips of alcohol or eating a portion of a donut), but the marginal utility decreases drastically after the immediate urge is satiated.

In the constraint equation, A_{2i} is the savings available for the second period; r is the asset return; c_{2i} is the total consumption in the second period; y_{1i} denotes i's income at period 1; θ_{1i} represents exogenous idiosyncratic shock on i's income at period 1. In the second

[10] Some people call this "keeping up with the Joneses" behavior. The function form of this peer consumption externalities varies, but the idea here only capture partial equilibrium effect without imposing strategic behaviors between own and the referenced group.

period, the period 2 self will maximize utility from consuming both goods and deviation payoff as defined before. At the last period, this consumption decision is subject to a budget constraint (i.e., $z_{2i} + x_{2i} = c_{2i}$, where $c_{2i} = A_{2i} + y_{2i}$). I can also write x_{2i} and z_{2i} into functions $x_{2i}(c_{2i})$ and $z_{2i}(c_{2i})$. χ describes the observability of the behavior, and is positive. The third term is associated with the payoff of self-image. $\overline{z_{1-ig}}$ is the average temptation consumption of i's group member at period 1 except household i's. Here, I assume that people weight each member's behavior in the group equally. In other words, they would like to appear to be social by acting in line with the group expectation. Peer's temptation consumption is assumed to be exogenous, and depends on the income shock of the social network group. The assumption of this deviation function is that $\frac{\partial \Phi(z_i, \bar{z}_{-ig})}{\partial |z_i - \overline{z_{-ig}}|} < 0$—the more household i deviates from the group behavior, the larger the disutility is.

To simplify the maximization problem, let $\Phi(z_i, \overline{z_{-ig}})$= - $\frac{1}{2}(z_i - \overline{z_{-ig}})^2$. This functional form is also used in Akerlof and Kranton (2002), where it captures student's utility loss from deviating from the predetermined ideal effort of the social category they belong. If the majority of group members consume a great deal of temptation goods, household i will have an undesirable feeling about herself if she consumes a small amount. The quadratic form weights deviation above and below equally, and can be imagined as social distance. Thus, if the behavior is highly observable (χ is large), an household's temptation consumption is expected to be in accordance with her peers' behavior. The maximization problem can be written as

$$\max_{x_{1i}, z_{1i}} u(x_{1i}) + v(z_{1i}) + \chi \left[-\frac{1}{2}(z_{1i} - \overline{z_{1-ig}})^2 \right] + \delta u(x_{2i}(c_{2i})) \tag{2}$$
$$\text{s.t. } A_{2i} = (1+r)(\theta_{1i} y_{1i} - x_{1i} - z_{1i})$$

Because $x_{2i}(c_{2i}) = x_{2i}(A_{2i} + y_{2i}) = x_{2i}[(1+r)(\theta_{1i} y_{1i} - x_{1i} - z_{1i}) + y_{2i}]$, and at the same time, $z_{2i} + x_{2i} = c_{2i}$, the first-order conditions with respect to z_{1i} and x_{1i} are:

$$v'(z_{1i}) - \chi(z_{1i} - \overline{z_{1-ig}}) + \delta u'(x_{2i}) \left(\frac{\partial x_{2i}}{\partial c_{2i}} \right) \left(\frac{\partial c_{2i}}{\partial z_{1i}} \right) = 0 \tag{3}$$

$$u'(x_{1i}) + \delta u'(x_{2i}) \left(\frac{\partial x_{2i}}{\partial c_{2i}} \right) \left(\frac{\partial c_{2i}}{\partial x_{1i}} \right) = 0 \tag{4}$$

Assuming a constant absolute risk aversion (CARA) functional form helps clarify the comparative static. $u(x) = -\frac{1}{\theta_x} e^{-\theta_x x}$ and $v(z) = -\frac{1}{\theta_z} e^{-\theta_z z}$. In addition, since $\frac{\partial c_{2i}}{\partial z_{1i}} = -(1+r)$ and $\frac{\partial x_{2i}}{\partial c_{2i}} + \frac{\partial z_{2i}}{\partial c_{2i}} = 1$, equation 3 becomes

$$z_{1i} - \frac{1}{\chi} e^{-\theta_z z_{1i}} = \overline{z_{1-ig}} - \frac{1}{\chi}(1+r)\delta e^{-\theta_x x_{2i}} \left(1 - \frac{\partial z_{2i}}{\partial c_{2i}} \right) \tag{5}$$

2.2 Predictions

The model generates the following comparative statics, where the full proofs refer to Section 8.

Prediction 1: *An increase in peers' temptation consumption will lead to an increase in household i's temptation consumption as long as the behavior is observable* ($\frac{\partial z_{1i}}{\partial \overline{z_{1-ig}}} > 0$ *if* $\chi > 0$).

The main interest here is to analyze $\frac{\partial z_{1i}}{\partial \overline{z_{1-ig}}}$. The prediction is driven by the deviation function. As long as the consumption behaviors are observable, an increase in peers' temptation consumption will lead to an increase in household i's temptation consumption because people suffer from behaving differently from their group norm.

Prediction 2: *Peer effect is stronger in temptation consumption, rather than in non-temptation consumption* $\left(\frac{\partial z_{1i}}{\partial \overline{z_{1-ig}}} > \frac{\partial x_{1i}}{\partial \overline{x_{1-ig}}}\right)$.

On the contrary, households' non-temptation consumption is not affected by their peers based on the implication of equation 4. This prediction is straightforward by the model construction, so I will test if this is a fair assumption. Suppose that peers' consumption on temptation ($\overline{z_{1-ig}}$) and non-temptation goods ($\overline{x_{1-ig}}$) are exogenous, household i's non-temptation consumption would not be affected by their peers.

Prediction 3: *Peer effects on temptation consumption are stronger when peers' consumption behaviors are more observable* $\left(\frac{\partial^2 z_{1i}}{\partial \overline{z_{1-ig}} \partial \chi} > 0\right)$.

This observability can be used to distinguish the magnitude of peer effects between consuming different types of goods. If peers' temptation consumption behaviors are more observable (higher χ), households' temptation consumption correlates more with their peers'. Based on the model prediction, social norms do not apply universally, but seem to be attached with the visibility of that behavior.

Prediction 4:
When households are poor, negative idiosyncratic shocks will increase total consumption ($\frac{\partial z_{1i}}{\partial \theta_{1i}} < 0$, *and* $\frac{\partial x_{1i}}{\partial \theta_{1i}} < 0$ *as consumption (c) is small);*
If one poor peer encounters adverse shock, other things being equal, this negative peer's shock has a positive impact on temptation consumption.[11]

[11] I can show this intuition based on specific assumptions, but the aggregate effect of peers' shock cannot

Another focus is the comparative static of consumption with respect to shocks – θ_{1i}. Assuming that θ_{1i} is exogenous, it is possible that a household would consume more temptation goods when encountering negative income shock. That is, $\frac{\partial z_{1i}}{\partial \theta_{1i}} < 0$ over a certain range of consumption. The reason for this property can be seen from equation 3 without applying any functional form in the mathematical appendix in Section 8.

The intuition can be viewed as increasing psychological barriers for the poor. The negative shock would make poor people be more desperate and less patient in consuming more now, rather than saving for the future. Many studies have found that poverty (or broadly speaking, scarcity) is associated with higher stress level, leading to worse cognitive performances (Chemin et al., 2013; Haushofer, 2011; Haushofer et al., 2011; Mani et al., 2013; Shah et al., 2012).

Following a similar logic, if one poor peer encounters negative income shock, assuming other things being equal, this effect will push up peers' average temptation consumption. Based on prediction 1, this increase in peers' average temptation consumption will further increase own temptation consumption.

In conclusion, I will be able to distinguish the mechanisms using the following predictions (An alternative risk-sharing mechanism is presented in the robustness check section. The comparison of predictions is in Table 1): (1) Peer effects happen mainly through temptation consumption. After controlling for peers' total consumption, peer effects on temptation consumption should still be significant based on the social norm model. (2) Peer effects are stronger in temptation goods than that in non-temptation goods. (3) The observability of consumption should matter if peer effects are through social norms. (4) Households' negative shock will have a counterintuitive positive effect on consumption because of the concave shape of temptation consumption among the poor. Poor peers encountering negative shocks should also create a similar positive effect on temptation consumption through social norm mechanism.

be generally proved.

3 Empirical Strategy

3.1 Assessing Endogenous Peer Effects

In this section, I will illustrate my strategies to overcome the identification challenges. Let me begin with my main mean regression model:

$$y_{it} = \alpha_0 + \alpha_1 y_{G_i t} + \alpha_2 X_{G_i t} + \alpha_3 X_{it} + u_{it} \tag{6}$$

y_{it} is the outcome variable (ex: per capita monthly consumption of temptation goods) of household i, with a peer group G_i. $y_{G_i t} = \frac{\sum_{j \in G_i, j \neq i} y_{jt}}{N_{G_i}}$ is the average outcome of i's peer group net of i's spending; N_{G_i} is the number of peers of household i, which is a fixed composition over time. The group-level temptation consumption does not include self's consumption. $X_{G_i t}$ is a vector of group characteristics. X_{it} is a vector of controls for household characteristics. u_{it} is the error term.

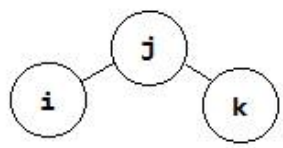
In the peer effect literature, α_1 is the endogenous peer effects (i.e. the effect of peer group's mean outcome), and α_2 captures the contextual effects (i.e. the effect of peer group's mean characteristics). The key task is to identify the endogenous peer effect. The literature has recognized three identification challenges: (1) reflection problem, (2) correlated effect and non-random selection, and (3) simultaneity.

Reflection Problem: This reflection problem, pointed out by Manski (1993), happens in linear in means models where the endogenous peer effect is a linear combination of all other regressors, and thus the endogenous peer effect is entangled with the contextual effect (Brock and Durlauf, 2001; Manski, 1993). In other words, the endogenous peer effect is perfectly collinear with the exogeneous peer characteristics. For example, if people in a small village are all friends with each other, I will not be able to identify α_1 because the group characteristics cannot be distinguished from the endogenous group behavior. Lee (2007) has formally shown that endogenous and contextual effect can be distinguished if there is sufficient variation in the size of peer groups. The seminal paper by Bramoullé et al. (2009) has proven Lee's case, as well as shown that the existence of intransitive triads (like our peers' of peers approach) can eliminate the reflection problem. Various empirical papers have used this concept to apply an instrumental variable approach to identify peer effects in different contexts. For example, De Giorgi et al. (2010) uses friends' of friends to study peer effects on the choice of college major; Nicoletti et al. (2018) uses women's family's neighbors to instrument peer effects on labor supply decision; Patnam (2011) uses peers-of-peers to identify corporate network effects.

Similar to the above literature, I use excluded peers' consumption as an instrument.

This approach makes sure that each person's peer group does not perfectly overlap, so as to overcome the reflection problem. As Figure 1 shows, households i and j interact with each other; households k and j interact with each other, but households k and i do not interact with each other. i's peer group (defined as G_i) includes all j. The excluded peer, household k, is in the network group with j, but not in the network group with i. Thus, i's excluded peer group (defined as K_i) includes all k, where k has to satisfy $k \in G_j$ and $k \notin G_i$. The information of the excluded peer group K_i can thus be used as an instrumental variable since j's peer group does not coincide with i's peer group.

Figure 1: Network illustration



Since in my analysis each household has different peer groups and groups mostly have different sizes, y_{G_i} cannot be a linear combination of all other regressors. This addresses the reflection problem. Also since the focal household does not directly connect with the excluded peers, the peer effect operates indirectly through this common friend—exclusion restriction condition for a valid IV. Even under a weaker assumption that i and j have a stronger interaction with each other than i and k, the peer effect can still be identified (De Giorgi et al., 2010).[12]

Non-random selection and correlated effect: Another concern is that people self-select their own friends, and thus the formation of peer groups can be endogenous. It is probable that people who love consuming temptation goods may happen to be more social and love to make friends with other social people. Researchers who fail to account for this endogenous formation factor may mistakenly think that peers' behaviors have perverse effects.

Similar to the solution in the literature, I further control for household fixed effects to absorb all the time-invariant unobservable characteristics to eliminate this assortative formation concern (Calvó-Armengol et al., 2009; Comola and Prina, 2015; Nicoletti et al., 2018; Patnam, 2011).[13] After controlling for household fixed effects, there is still a concern

[12] They show that with some extent of measurement error (i.e. k may in fact interact with i), the estimation is still unbiased.

[13] Patnam (2011) uses first-difference to eliminate time-invariant non-random selection. As my data has multiple periods, I use household fixed effect instead. Comola and Prina (2015) use the dyad-specific fixed

of other time-varying factors—there may be unobservable common shocks that happen to the whole group and drive people's temptation consumption behaviors. People consume more temptation goods in religious ceremony or holidays, for example, lunar new year in Thailand. In addition, one can imagine some common village-level economic shocks that drive the temptation consumption pattern, say people drink more during a good harvest. I control for village-year fixed effects and seasonal effect to take care of these confounding factors.

The resulting estimation incorporating the above strategies is:

$$y_{ivst} = \alpha_1 y_{G_i vst} + \alpha_2 X_{G_i vst} + \alpha_3 X_{ivst} + h_i + season_s + f_{vt} + \zeta_{ivst} \tag{7}$$

I use household fixed effects h_i to control for time-invariant household fixed demographic characteristics. Seasonal fixed effects ($season_s$) eliminate any seasonal consumption pattern that could be confounded with identifying the endogenous peer effects. Village-year fixed effects (f_{vt}) are also taken into account to prevent from capturing a systematic consumption pattern at the village-year level. After controlling for these necessary covariates, my identification comes from a household's peers' monthly change in consumption within the same village-season-year.

Simultaneity: This challenge refers to that people and their friends may make decisions simultaneously. To address this problem, I use lagged consumption behaviors as the instrument. It is plausible to assume that a household's contemporary decision cannot affect peers' previous consumption. This is a common strategy to solve the simultaneity problem in the network literature (Bramoullé et al., 2009; Calvó-Armengol et al., 2009; Comola and Prina, 2015; Drukker et al., 2013; Kelejian and Piras, 2014; Patacchini and Zenou, 2009; Quintana-Domeque and Wohlfart, 2016).[14] For the lagged instrument to work, I need an assumption that this spillover effect of consumption behaviors takes some time for one to adopt. The monthly lag I use in my estimation is a reasonable time frame because empirical

effect in their estimation, which, in their two-period model, is similar to a first-difference estimation. Nicoletti et al. (2018) uses an average of all neighbors' working hours which is similar to the network fixed effects, and is qualitatively similar to my purpose here. Some use network fixed effects instead, and this identification strategy is similar to our household fixed effects. For example, Calvó-Armengol et al. (2009) absorb sorting based on unobservables using what they called "(pseudo) panel data-fixed effects estimator" to subtract the network average from the individual-level variables. This approach yields the same effect as using household fixed effects.

[14] In Quintana-Domeque and Wohlfart (2016), they claimed that "*We instrument the growth in rich consumption with lagged variables, since under rational expectations the forecast error will be uncorrelated with all the available information in the prior year.*" However, they did not specifically say that this strategy is to eliminate simultaneity problem.

data shows that consumers' utility can exhibit some level of habit formation—a theory which captures the fact that current utility depends on current consumption relative to the lagged consumption, and thus cause the delay of consumption response to shocks (Fuhrer, 2000). I use habit formation to justify my empirical strategy, but do not explicitly incorporate it into the theoretical model because this part of modeling is beyond the scope of this paper. Nevertheless, I test this assumption using a more symmetric time frame in the robustness check section.

Other threats to identification: Other remaining threats to identification include any non-random unobservable time-varying factors that either confound with the network formation or the decision making of the outcome. Even though this endogenous network formation/interaction cannot be fully ruled out, I argue that it is not likely to be a problem because of the following reasons.

First, it is fair to assume that social group formation in the village is not perfectly linear with a household's decision making on consumption conditional on all the covariates. The social relations in Thai villages tend to be quite stable, so it is unlikely that these relations coincide with people's monthly change in consumption after controlling for such a large set of fixed effects.

Second, in one of the empirical estimation, I use excluded peers' idiosyncratic shock variable as an instrument to further evaluate this problem. Given that excluded peers' idiosyncratic shocks can induce more temptation consumption as predicted by Banerjee and Mullainathan (2010) and are at the same time time-varying, this instrumental variable is orthogonal to households' choice of friends as well as the consumption behaviors.[15] As the peer effect on temptation consumption is still significant in this specification, I have more confidence in my identification strategy.

Finally, it is possible that the excluded peers affect households' own temptation consumption, but not households' peers–one scenario that violates the exclusion restriction. For example, I am told by my friend that one of her friends had enjoyed drinking and gambling a lot recently. I am influenced by this piece of information and increase my consumption of those goods, while my friend does not. This scenario is unfortunately not testable. Yet, temptation consumption behaviors are a type of behavior that happens repetitively in the villages and does not demand much information. It is unlikely that households react to

[15] Although one could imagine that if someone was sick last month, people stop inviting them to the party to drink together, making the peer effects attenuated. This is not what we find. We find that shocks translate into more temptation consumption, so as translate into peer effects on temptation. So if this were to happen, this concern will only make my results stronger.

excluded friends' behavior that their direct friends do not respond to. Also, other information channels, for example a price discount of certain temptation goods, are controlled by seasonal and village-year effects.

3.2 Estimation

Following all the identification strategies to address endogeneity, we estimate a standard 2SLS approach. The first-stage regression for the peer group is:

$$temp_{G_ivst} = \beta_1 Z_{K_ivst-1} + \beta_2 X_{G_ivst} + \beta_3 X_{ivst} + h_i + season_s + f_{vt} + \eta_{G_ivst} \tag{8}$$

where $temp_{G_ivst}$ is the average spending amount on temptation goods of i's peer group G_i in village v season s at time t; Z_{k_ivst} is the average temptation consumption of household i's excluded peer group K_i in village v season s at time $t-1$; X_{G_ivst} are peer attributes; X_{ivst} are appropriate household controls; h_i are household fixed effects; $season_s$ are seasonal fixed effects; f_{vt} are village-year fixed effects; and η_{G_ivst} is the error term.

The second-stage regression is:

$$temp_{ivst} = \delta_1 \hat{temp}_{G_ivst} + \delta_2 X_{G_ivst} + \delta_3 X_{ivst} + h_i + season_s + f_{vt} + \varepsilon_{ivst} \tag{9}$$

where $temp_{ivst}$ is the per capita monthly temptation consumption of household i in village v season s at time t. The rest of the variables are the same as the first-stage regression. The main interest is δ_1, which is hypothesized to be greater than zero.

3.3 Empirical Predictions for Social Norm Mechanism

In addition to the prediction on δ_1, the theory also generates several other predictions, which I reiterate in this section. All the regressions are estimated using this similar instrumental technique.

Peer effects on temptation: Based on Prediction 1, peers' temptation consumption should affect a household's own temptation consumption. $\delta_1 > 0$ in equation 9. This peer effect should still be significant even after controlling for peers' total consumption. This property can be helpful to distinguish from the alternative mechanism: risk sharing. The predictions of the alternative risk-sharing theory will be presented in Section 6.1. For example, I estimate the following specification:

$$temp_{ivst} = \gamma_1 temp_{G_ivst} + \gamma_2 cons_{G_ivst} + \gamma_3 X_{G_ivst} + \gamma_4 X_{ivst} + h_i + season_s + f_{vt} + \varepsilon_{ivst} \tag{10}$$

where $cons_{G_ivst}$ is the average per capita monthly total consumption of household i's peer group G_i in village v season s at time t. Therefore, $\gamma_1 > 0$.

Non-temptation consumption v.s. temptation consumption: Replacing temptation consumption with non-temptation consumption in equation 7 can also help distinguish motivations. Based on Prediction 3, the coefficient of peers' temptation consumption should be greater than that of peers' non-temptation consumption if the mechanism is through social norm. The logic here is that the social-norm model predicts that people imitate peers' temptation consumption, rather than regular (non-temptation) consumption. Run the following regression:

$$nontemp_{ivst} = b_1 nontemp_{G_ivst} + b_2 X_{G_ivst} + b_3 X_{ivst} + h_i + season_s + f_{vt} + \xi_{ivst} \tag{11}$$

where $nontemp_{ivst}$ is the per capita monthly non-temptation consumption of household i in village v season s at time t, and $nontemp_{G_ivst}$ is the average per capita non-temptation consumption of household i's peer group G_i in village v season s at time t. b_1 is expected to be less than δ_1.

Observability: According to Prediction 3 from my model, peer effects are stronger for temptation goods that are more observable. Higher observability (χ) of peers' temptation consumption may induce a larger conformity effect on own temptation consumption because of the larger utility loss of deviating from others. For example, alcohol consumption outside is more observable than alcohol consumption at home.

$$\begin{aligned} alcoholTOTAL_{ivst} =& \gamma_{temp_H} alcoholHOME_{G_ivst} + \gamma_3 X_{G_ivst} + \gamma_4 X_{ivst} + h_i \\ &+ season_s + f_{vt} + \varepsilon^H_{ivst} \end{aligned}$$

$$\begin{aligned} alcoholTOTAL_{ivst} =& \gamma_{temp_O} alcoholOUT_{G_ivst} + \gamma_3 X_{G_ivst} + \gamma_4 X_{ivst} + h_i \\ &+ season_s + f_{vt} + \varepsilon^O_{ivst} \end{aligned}$$

where $alcoholHOME_{G_ivst}$ is the average per capita alcohol consumption at home of household i's peer group G_i in village v season s at time t; $alcoholOUT_{G_ivst}$ is the average per capita outside alcohol consumption of household i's peer group G_i in village v season s at time t; $alcoholTOTAL_{ivst}$ is household i's total alcohol consumption, including at home and outside, in village v season s at time t.

In the above equation, the coefficient of peers' temptation consumption outside should be greater than that of peers' temptation consumption at home because the former is more observable than the latter. Thus, γ_{temp_O} is expected to be greater than γ_{temp_H}.

I also run similar specification, but using $alcoholHOME_{ivst}$ as the dependent variable, where $alcoholHOME_{ivst}$ is household i's per capita alcohol consumption at home in village v season s at time t. This specification is to test whether this consumption norm has spillover effects on households' own alcohol consumption at home. I expect similar prediction that

γ_{temp_O} is greater than γ_{temp_H}.

Shock event: Idiosyncratic shocks cause different effects on a household's consumption (Prediction 4 in Section 3.2). In the social norm model, the shape of the temptation would matter because people face trade-offs between the present and the future period. At the consumption level where households are myopic, positive (negative) shock would have a negative (positive) effect on consumption, especially for the poor (i.e., $\beta_{temp2} > 0$, $b_{nontemp2} > 0$). Here the larger the shock variable ($shock_{ivst}$), the worse the shock is. At the same time, poor peers' shock would have the same effect on temptation consumption through social norms mechanism (i.e. $\beta_{temp1} > 0$):

$$\begin{aligned} temp_{ivst} =& \beta_{temp1} shock_{G_i vst} + \beta_{temp2} shock_{ivst} + \beta_{inc} poor_{ivst} \\ &+ \beta_c poor_{ivst} shock_{ivst} + \beta_3 X_{G_i vst} + \beta_4 X_{ivst} + hi + season_s + f_{vt} + \epsilon^{temp}_{ivst} \\ nontemp_{ivst} =& + \beta_3 X_{G_i vst} + b_4 X_{ivst} + hi + season_s + f_{vt} + \epsilon^{nontemp}_{ivst} \end{aligned}$$

where $shock_{ivst}$ is per capita average days of health shock of household i in village v season s at time t, $shock_{G_i vst}$ is the aggregate days of health shock among household i's peers G_i who are under the poverty line in village v season s at time t, excluding household i's own shock, and $poor_{ivst}$ is household i's poverty status in village v season s at time t. Notice that I do not further control for the number of friends, because it does not change over time and I have controlled for household fixed effects (h_i). But peers' poverty status can be different over time, so I further control for the time-varying number of poor peers as a comparison.

Since idiosyncratic shock has a positive impact on people's consumption when people are poor enough, the shock and poor interaction term should be positive ($\beta_c > 0$ and $b_c > 0$). Poor people appear to be more myopic so that shock would have a positive impact on their consumption.

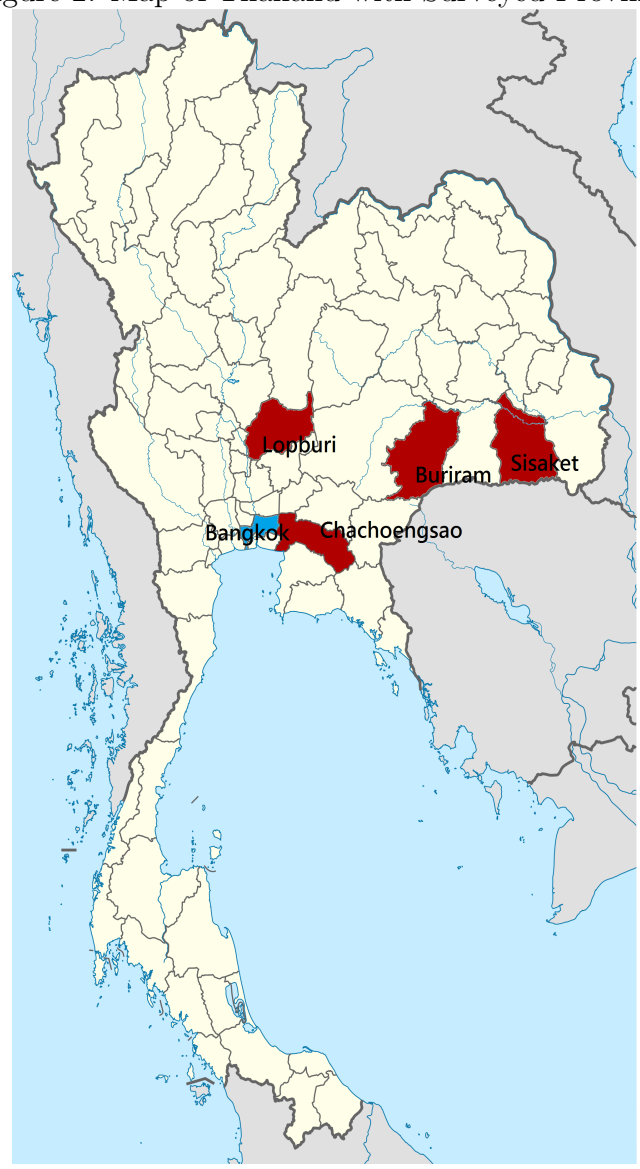
4 Data

4.1 Dataset Description

The study uses data from the 1999 to 2004 monthly waves of the Townsend Thai Monthly Survey. The continuously observed sample size is 480 in all 72 months. The survey was conducted in 16 villages, four in each of four separate provinces. As Figure 2 shows, two provinces (Chachoengsao and Lopburi) are close to Bangkok, and the other two (Buriram and Sisaket) are in the northeastern rural region close to the Cambodian border. The success rate of the survey (the number of households that were successfully surveyed out of the total

number of households in each month) is at least 93%. However, because some households migrate permanently during the survey period, they are replaced by other randomly selected households in order to make the sample representative of the village.

Figure 2: Map of Thailand with Surveyed Provinces



The data include households' demographic characteristics, expenditure, and income. There is also detailed information on financial, gift exchange, and labor-sharing relationships. All these transactional relationships are time-varying. The monthly temporal scale is a valuable feature of the dataset since consumption data are difficult to recall, and the frequent data collection reduces measurement error. In addition, the expenditure informa-

tion is comprehensive, including categories such as various food items, oil and fat, sugar and sweet, beverages, alcohol, tobacco, gambling, etc.

4.2 Social Network Data

I categorize household-level social networks using their actual transactions (rather than hypothetical), including borrowing and lending, gift-giving, and labor sharing over a long period of time. The transaction relation helps us capture the actual, rather than a proxy for, social networks with whom people truly interact. I believe that this concrete definition largely reduces the amount of measurement error without subjective evaluations. The repeated monthly observations, which is a very rare survey design, also reduce the recalling measurement errors to collect a more complete network. As people socialize beyond the naturally formed boundaries, such as neighbors, blood relations, or co-workers, I can capture those who people actually spend time with through labor sharing relations, and those who people actually care enough to involve monetary transactions with. It is also reassuring that this definition helps capture the underlying friendship relations as gift-giving, borrowing, and labor sharing transactions happen quite common among friends in Thai villages (Kinnan and Townsend, 2012).[16]

Based on these transactions, I construct a matrix called $\mathbf{G}$, where $\mathbf{G}_{ij} = 1$ if household i is linked with j, for any $j \neq$ i. Households who have ever had any of these relationships within the survey period are categorized as being connected. In other words, the social network is defined by the aggregation of all the transaction relations a household i has through financial relationships, gift exchange, and labor-sharing relationships over 72 months. Here I assume symmetry ($\mathbf{G}_{ij} = \mathbf{G}_{ji}$), or so-called undirected network. If a household is linked in one direction, I assume that they can be linked in the other way around to eliminate the survey errors—a standard solution in the literature.[17] For example, i reports that he/she has borrowed from j, so j should be within i's social network ($\mathbf{G}_{ij} = 1$). However, it may happen that j did not report i in any of the social relations. It is very likely that i is indeed within j's social network as well, but j forgets to report his relationship with i. It is less

[16]Kinnan and Townsend (2012) noted that financial transfers and gift-giving in Thai villages are prevalent among family and friends. Also, in the data, I find that households exchange labors with their friends. The survey asks household to identify those who they have a labor sharing relationship with, and then explain the nature of the relationship, for example, neighbor, relatives, or friend.

[17]Literature has shown this kind of discordant response in the network survey (Banerjee and Mullainathan, 2007; Comola and Fafchamps, 2013; De Weerdt, 2004; De Weerdt and Fafchamps, 2011; Fafchamps and Lund, 2003; Liu et al., 2012). Among those, Comola and Fafchamps (2013) has a thorough discussion on the treatment of discordant link.

possible that i lies about his relationship with j.[18] This asymmetry assumption is reasonable to capture maximum network interactions based upon the best available information in this data.

Why do I collapse all the transaction data into time-invariant networks, instead of dynamic networks? This definition is followed by the idea in Kinnan and Townsend (2012) using the same data.[19] Two reasons are in order. First, the network in Thai villages is mostly long-term and stable as people have lived in the same village throughout their lives. According to the survey document from the Thai Townsend survey, most of the migration is only temporary (completed within 5 months), and the longer term migration is very rare.[20] Second, the survey asks people about their actual transactions with other villagers, instead of listing out all the potential friends. These transactions do not happen instantaneously and may only happen on a need basis. For example, I do not need to share labors with my friend j at month t, but I share labors with her at month $t+1$. Not observing a link between me and my friend j at time t does not mean that we are not friends at time t.[21] I consider this approach capturing the underlying peer networks people are embedded in.

I list some other advantages of using this network data. First, the high-frequency collection of the data makes sure that using the excluded network is a valid IV approach that household i is only influenced by k through this common friend j's effect. Even though our network definition can still exist measurement errors, it is reassuring that if two households have never had any transactions with each other in any of the 72 months, they are not likely to know or even care with each other to exhibit a peer effect—the necessary exclusion restriction condition. Second, our network measure in the context of a developing country is

[18] Although Schechter and Yuskavage (2011) show empirically that social networks with reciprocated relationships may have different features from those with unreciprocated relationships, their result does not provide a prior on how this might affect temptation consumption. In addition, their definition of reciprocal is whether money flows in both directions, while mine is whether both parties agree on the relationship.

[19] Their paper focusing on the financial network as they care about borrowing and saving behaviors. Yet I believe their approach is a good reference capturing the nature of the relationship in the Thai villages.

[20] The summary of the monthly survey document can be found on the Townsend Thai Project's website: https://goo.gl/wDARZG.

[21] Some recent papers using dynamic networks to further help with identification in other contexts. While this dynamic network definition is useful, the definition of a dynamic network in many contexts is not free from assumption. For example, Comola and Prina (2015) uses observed financial transactions (similar to the survey approach in our project) to define a dynamic financial network in baseline and endline to study network effects on a saving intervention experiment in Nepal. Maybe the network context in Nepal is different from Thailand. But this seem-to-be dynamic network may be in fact the inability to capture some relations in the baseline because those transactions do not happen instantaneously. Comola and Prina (2015) themselves claim the caveat of this definition in the paper: "*However, by using questions on actual transfers, we may be overlooking silent links that do not get activated during the time of our study.*"

relatively more credible than in a developed world. In the context of developing countries, for example, in rural Thailand, people seldom socialize with those who are far away because of monetary or technological barriers. So the social relations captured within a village in my context is more complete than that in an urban developed world.[22]

4.3 Key Variables of Interest

The key outcome variable is the expenditure on temptation goods. Since the detailed monthly survey provides the possibility of separating consumption into different categories, I use household's expenditure on alcoholic beverages (at home), alcoholic beverages (consumed away from home), tobacco, lottery, and gambling.

The key explanatory variable is the consumption spending of the people within the network. I calculate mean temptation consumption within household i's network ($\overline{z_{-ig}}$) as the proxy for this. The mean temptation consumption for household i's network is the aggregate household j's temptation consumption conditional on the information of $\mathbf{G}$ and divided by the network sample. Other explanatory variables, for example, the peers' shock variable, are defined similarly. Peers' health shock, which is used as a proxy for income shock θ, is the aggregate household j's days of sickness per capita conditional on the information of $\mathbf{G}$ and divided by the network sample size.

4.4 Summary Statistics

Summary statistics from the Thai dataset are presented in Table 2. It is worth noting that households spend a significant amount on temptation goods, which consists of seven percent of total consumption on average. The yearly expenditure on temptation goods is equivalent to households' average yearly spending on education. Figure 4 shows that there is variation among different households in terms of their spending on temptation goods.

Among the total 480 observations, 374 people can be linked with at least one peer within the same tambon (an administrative level above village). On average, the network size is five, mostly neighbors and relatives.

Table 3 shows simple correlations of the characteristics between villagers and their peers. People within the same network have similar income level, household size, and percentage of their agricultural income. The correlation on the percentage of agricultural income is

[22] With the prevalence of social media, people can socialize on line with others in another country. So in this context, social network measure is harder because even if we capture everyone's network information within a city, we still miss a large amount of the information outside of this geographic boundary.

especially strong. This implies that people tend to have networks composed of individuals with the same occupation. This may be because people who have labor-sharing relationships are specialized in the same economic activity. In terms of idiosyncratic health shock, peers' health shock is much less correlated.

5 Empirical Results

Almost all the results using the instrumented social network information support the theory of social norm. In most of the cases, the instrument is valid with very high F-statistics in the first stage.[23] The results using instrumental variables are similar to that using OLS. Even though some observations are missing using the excluded network as instruments, this consistency yields high confidence of the results.[24]

5.1 Peer Effects on Temptation and Non-temptation

Table 4 presents the OLS and IV results. The coefficient in column 3 of Table 4 indicates that own temptation consumption is affected by peers, and the magnitude of peer effects on temptation consumption is also remarkable. One extra baht of peers' average monthly spending on temptation goods can lead to 1.5 bahts of own temptation consumption in the IV specification using clustered standard errors, wild clustered bootstrap adjustment, and robust standard errors without clustering (not shown here). Because of the weak instrument, I further test the results using the Conditional Likelihood Ratio test, which reports reliable results under a weak instrument. The results remain robust as the CLR test suggests positive confidence intervals.

The coefficients in the IV specification are higher than the OLS coefficient. It means that the correlated effect (in the disturbance term) that OLS coefficients pick up actually runs in the opposite direction from the peer effect. The higher IV is not unique in this study as De Giorgi et al. (2010) also found this similar result. They explain that each unobserv-

[23]The exception is in the table analyzing peer effects on temptation and non-temptation consumption. The F-statistics in the first stage are not high because peer effects do not happen in non-temptation consumption. With respect to the weak instrument for temptation consumption, I further use the Conditional Likelihood Ratio (CLR) test to report the robust confidence intervals under weak instruments. According to Andrews et al. (2008), CLR test is more optimal than Anderson and Rubin (AR) statistics and LM statistics, which are both robust statistics under weak instruments.

[24]In order to use a friend of a friend as the instrument, there should exist such kind of the third person k between two people, say, i and j. However, there is a missing instrument for the case when i is the only friend of j, and at the same time, j is the only friend of i.

able common shock can have a different sign, so OLS coefficients are not unambiguously larger than the IV estimators. In addition, the peer group is not perfectly overlapped, so the simultaneity issue is much eliminated in the OLS case compared with using a totally overlapped social network definition.[25] Caeyers and Fafchamps (2015) further introduce the so-called "exclusion bias" to explain why OLS estimates of endogenous peer effects are larger than their estimated IV counterparts. They illustrate that the exclusion bias occurs naturally when researchers exclude individual itself from its own peers, and this construction will create a downward bias in the OLS estimate, rather than an upward bias. For example, if individual i has a higher than average ability relative to its peers, excluding i will make the average ability of i's peers lower, resulting in a negative correlation between i's characteristics and the average characteristics of i's peers. The other reason for the relatively larger IV estimators than OLS estimators can be due to my weak instrument. This lower correlation between instrumental and instrumented variables can inflate IV estimators. Columns 1 to 4 show that the coefficients of peers' temptation consumption are higher than that of peers' non-temptation consumption. Since the signs of the coefficients using IV and OLS regressions are in the same direction, these results corroborate the social norm mechanism that individuals suffer from disutility when deviating from the average temptation consumption of their peers.

Columns 5 and 6 of Table 4 present the consumption relationship between own and peers, but controlling for peers' total consumption. This test aims to rule out the alternative risk-sharing hypothesis where peer effects should go away once controlling for peers' total consumption (a detailed explanation of the prediction on alternative risk-sharing mechanism is presented in Section 6.1). The results serve as another piece of evidence to support social norm mechanism: peer effects on temptation consumption remain positive and significant when controlling for peers' total consumption. The coefficient on peers' temptation consumption is around 1.6. The coefficient on peers' non-temptation consumption is much smaller and insignificant controlling for peers' total consumption. All the results in Table 4 are consistent with Predictions 1 and 2 in social norm theory.

[25] For example, if one uses village as the social network definition, then, within a network, everyone's social network overlaps entirely. The aggregation of each individual within the network group comprises the group itself.

5.2 Observability

Table 5 presents peer effects of alcohol consumption at home versus alcohol consumption outside. The results support Prediction 3 in the social norm theory—peer effects are much more significant among more observable consumption. Columns 1 to 4 show the effects of peers' alcohol consumption outside versus peers' alcohol consumption at home on household's total alcohol consumption. Columns 1 and 2 present the results from OLS specification, and columns 3 and 4 present the results from IV specification. The results indicate that the coefficients of peers' alcohol consumption outside are stronger than that of peers' alcohol consumption at home—consistent with the social norm theory. It is worth noting that the instrument on peers' alcohol consumption at home is relatively weak, and therefore the coefficient may be inflated. The weak instrument issue is not worrisome nonetheless because peers' alcohol consumption at home is less observable and thus generate smaller peer pressure. By comparing the OLS coefficients in columns 1 and 2, I am confident that peers' alcohol consumption outside has a qualitatively stronger influence than peers' alcohol consumption at home. Columns 5 and 6 are the coefficients of peers' alcohol consumption on the household's home consumption. As expected, columns 5 and 6 have similar results as in columns 3 and 4, given that this social norm of peers' drinking behavior should have a spillover effect on the household's home alcohol consumption. Columns 7 and 8 present similar analysis as in columns 3 and 4, but controlling for peers' total consumption. The coefficient on peers' alcohol consumption outside is qualitatively larger and more statistically significant than that at home after controlling for peers' total consumption. Overall, one extra baht of peers' average monthly spending on alcohol outside is associated with 4.3 bahts of individual's monthly spending on total alcohol. Since alcohol consumption outside is likely to be more observable than alcohol consumption at home, the results verify that the deviation function plays a more important role in maximizing individual utility when peers' behaviors are more observable.

5.3 Shock Event

Table 6 presents the effect of peers' idiosyncratic shock on consumption patterns. Here health shock is the proxy for income shock, and is measured as total days of sickness of the household.[26] So the larger the number, the more adverse the shock is. As income may be endogenous to the consumption pattern, health shocks can capture a more exogenous

[26]Health shock is significantly correlated with income. One percentage increase of sickness decreases income by three percent.

variation. Overall, people's consumption pattern in the event of health shocks also supports the predictions in the social norm theory. Since the peers' shock variable is not subject to the simultaneity problem, I use the contemporaneous shock variable of i's excluded network to instrument peer effects (the signs and magnitude are the same using shock variables at period $t-1$ as the instrument). As health shocks are idiosyncratic and people are less subject to correlated effect, I also present the non-instrumented OLS result as a comparison.

According to Prediction 4 in the social norm theory, poor peers' negative shock should have positive effects on own temptation consumption through the conformity effect. The first row in columns 1 3 and 5 should be, in theory, positive and significant. As expected, all of these coefficients are positive. The coefficients in the IV specification are significantly different from zero. Notice that peers' adverse shock has a much stronger positive impact on household's own temptation consumption than that on household's non-temptation consumption. The difference between columns 3, 4 and columns 5, 6 is the extra control for the number of poor peers. Although the number of poor peers may be endogenous, these results in columns 5 and 6 help me to validate that the results in row 1 are not mainly driven by those who have more poor friends in their networks. In conclusion, one extra day of poor peer's sickness within a month can increase household's per capita monthly temptation consumption by one bhat.

Furthermore, own health shock should have a positive effect on both temptation and non-temptation consumption among the poor, meaning that the interaction term of poverty status and health shock in row 4 should be positive. Table 6 shows that poor households appear to be more myopic by consuming more temptation goods, relative to the rich. The positive effect of negative shocks on consumption would be more likely among the poor than the rich. In the results using both OLS and IV, the coefficients on $poverty_{ivt} * shock_{ivt}$ in columns 1, 3 and 5 are positive among temptation consumption; however, the coefficients on $poverty_{ivt} * shock_{ivt}$ in columns 2, 4 and 6 are negative among non-temptation consumption. These results indicate that, in the event of negative shocks, the poor would choose to spend much less in non-temptation consumption relative to the rich, while cutting down much less on temptation consumption compared with the rich. Poor households seem to be less resistant to temptation goods. If we view consuming temptation goods as a sign of impatience, the evidence slightly supports income heterogeneity of the myopic behavior. Take column 5 for example, one extra day of sickness can decrease rich households' temptation consumption by 0.182 bahts, while one extra day of sickness only decreases temptation by 0.0874 bahts among the poor households.

6 Robustness Check

6.1 Alternative Model: Risk-Sharing Model

Could this observed peer effect be explained by another mechanism, for example, risk sharing (Townsend, 1994)? A household's social network provides risk-sharing function, which makes people borrow and lend from the same pool of money. Although there are various ways to test risk-sharing, the most important predictions should be that individuals' consumption comoves with their peers $\frac{\partial z_{ist}}{\partial(\overline{x_{st}}+\overline{z_{st}})} > 0$. This risk-sharing mechanism leads to similar peer effects on individuals' temptation consumption as the social norm model. However, this comovement happens not only for individuals' consumption in temptation goods, but also in non-temptation goods. That said, once we control for the total consumption of peers, this comovement between peers' and individuals' temptation consumption would no longer hold. This is one way we can distinguish the risk-sharing mechanism from social norm mechanism.

Another way to distinguish the risk-sharing mechanism from the social norm mechanism is through the prediction of shocks. The risk-sharing model would have predictions similar to Fafchamps and Lund (2003): (1) Shocks affecting network members will decrease an individual's consumption (both temptation and non-temptation consumption). (2) Idiosyncratic shocks have no impact on individual's consumption (both temptation and non-temptation consumption) once controlling for network shocks.

In conclusion, the social norm model yields different results from the risk-sharing model in Predictions 2–4. Table 1 illustrates the differences. First, both models predict a positive correlation between own and peers' temptation consumption. In the second prediction: risk-sharing model predicts that the coefficient on peers' temptation consumption is no longer significant after controlling for peers' total consumption. Third, the coefficient on peers' temptation consumption is the same as that on peers' non-temptation consumption in the risk-sharing model, while the coefficient on peers' temptation consumption is significantly larger than that on peers' non-temptation consumption in the social norm model. Fourth, there is a significant difference between more observable consumption and less observable consumption in the social norm theory; peer effects would be stronger on alcohol consumption outside than alcohol consumption at home. The risk-sharing model does not distinguish those two consumption behaviors. With respect to the income shock in the fourth prediction, peers' shock will have negative effects on own temptation and non-temptation consumption in the risk-sharing model, but peers' negative income shock, in contrast, will increase own temptation consumption through the social norm mechanism. In the social norm model,

idiosyncratic shocks will also have positive effects on the total consumption. In the risk-sharing model, idiosyncratic shocks will not play a role in own consumption if we control for peers' aggregate shock. Our results, consistent with the predictions from the social norm model, validate that social norms would be a more probable explanation than the risk-sharing theory.

6.2 Other Robustness Checks

The previous section contrasts the predictions between the risk-sharing and the social norm model. This section presents several robustness checks. My results support social norms. However, to make sure that I did not process the data differently than the previous literature using the same information, I use village as the social network definition to test the risk-sharing theory. Similar to Townsend (1994), I use the aggregate yearly data to run the analysis on the household's idiosyncratic income against household's consumption. If risk sharing is in place and efficient, the coefficient on idiosyncratic income should be small and insignificant.

Table A-1 shows the relationship between own income and consumption. The results in columns 1 and 2 indicate the existence of risk sharing at the village level. The coefficient in column 1, although significant, is quite small. The coefficient in column 2 using first difference specification is small and insignificant. Idiosyncratic income is not correlated with consumption. Yet village is a very crude definition for the social network. When it comes to people's consumption behaviors, it is more important to understand the peer groups with whom people have close interaction. Social norm strongly affects villagers' temptation consumption when observing the behaviors of individuals' peer groups.

I further conduct robustness check using variables with a different time frame. This alternative analysis sheds additional light on the mechanism because the lagged instrument may require a habit formation assumption in addition to peer effects. One may also worry about the asymmetry of the timing that I use lagged consumption to instrument peers' current-period consumption at the first stage[27], while using both peers' and own consumption variables at the current period. To test whether the results are still robust with a symmetric time frame, I use consumption at time $t-2$ to instrument peers' consumption at time $t-1$ in the first stage, and then use this predicted $t-1$ variable on own consumption variable at time t. I expect the results to be similar using this symmetric specification because there can be a delay in response to peers' temptation consumption, assuming habit formation in consumers'

[27]Initially, I use a lagged variable to eliminate the simultaneous decision making of own and peers.

utility function. Table A-2 shows that using variables with a different time frame, we observe similar peer effects on temptation consumption, and the results are weaker compared to the previous results using instruments at $t-1$ in table 4. In column 3, for example, the coefficient is at the borderline of significance. Table A-3 includes results using alcohol consumption with the similar time frame as explained above. The results in this table are consistent and robust as well.

Another caveat of the analysis is that the data are sampled within the village. Identification may be compromised by using sampled networks (Chandrasekhar and Lewis, 2011). They show that even if network members are sampled randomly, this partial sampling will lead to nonclassical measurement errors, and can bias the estimation. Because of the concern of mis-measured social networks, I sampled 50 percent of my observations to re-run the analysis. Although I cannot recover all the non-sampled network information, this robustness check can gauge whether the result is strong and stable enough even with some level of missing network information. The results are presented in Table A-4 to Table A-6. All results stay the same. The robustness of the results from 50 percent of the sample reduces the concern of using sampled social networks.

Some may challenge the observability test between "alcohol consumption at home" and "alcohol consumption outside"; people may gain individual utility by simply "drinking with their friends." This alternative can contradict with the definition of "temptation" good that people do not gain utility from thinking about future consumption at present. To address this concern, I verify the result using temptation consumption excluding alcohol consumption. The specification I can use is similar to the test in observability. Instead of alcohol consumption, I use $tempExAlcohol_{ivt} = \delta_0 + \delta_{temp_O} tempExAlcohol_{G_ivt} + \delta_3 X_{ivt} + f_{vt} + \xi_{ivt}$, where $tempExAlcohol_{ivt}$ represents an individual's monthly temptation consumption excluding alcohol consumption, and $tempExAlcohol_{G_ivt}$ is i's peers' average monthly temptation consumption excluding alcohol consumption. Then I use the same specification controlling for peers' average total monthly consumption.

Table A-7 presents the result of peer effects on temptation consumption excluding alcohol consumption. Column 1 indicates that peers' temptation consumption excluding alcohol consumption has a significant impact on an individual's. The coefficient on peers' temptation consumption (excluding alcohol) is around 1.6. The positive sign still holds in column 2 even after controlling for peers' total consumption, although it is only close to 10% significance level. Assuming that people do not gamble or buy lotteries together, the significance of the result using temptation consumption on gambling/lottery buying verifies the social

norm hypothesis. Based on the anecdotal evidence, people in those Thai villages usually go gambling by themselves. There are also multiple types of informal gambling, such as buying lotteries, betting on stock prices and fish/chicken fights. Individuals usually give a bet at the local stores. The result further confirms that the peer effects of alcohol consumption are not simply driven by the joy of consuming together.

Temptation spending captures people's myopic consumption allocation. Based on Banerjee and Mullainathan (2010), the concave shape of temptation will have an impact on an individual's saving. So I further test whether peer effects on temptation spending would affect saving behaviors. Based on the availability of the data,[28] I use whether any household members have a saving account to approximate saving behaviors. Table A-8 shows that peers' temptation spending further hinders an individual's saving behavior. The confidence interval using the CLR test falls entirely in the negative range. Although the IV coefficient is not significant, the CLR test gives a more robust result under weak instruments.

7 Conclusion

Self-control problems lead individuals to consume multiple types of temptation goods, and this consumption behavior is primarily influenced by peers; thus, the "self-control" problem is, in essence, a "group-control" problem. To examine peer effects on temptation consumption, I present a social norm model to motivate the empirics. The social norm model asserts that people have a tendency to emulate the temptation consumption of the majority. The extent of this conforming behavior varies with the observability of the consumption. The analysis reveals that even when peers' total consumption is controlled, peer effects can still be found on temptation consumption.

Using comprehensive survey data from Thailand, I instrument peer effects on temptation consumption through the excluded peers' temptation consumption. The data, collected on a monthly and weekly basis, include important information on social relations, a variety of sources of income, and several types of consumption. The empirical results show that peer effects on temptation consumption are driven mainly by social norms: people's temptation consumption varies with the consumption of their peers because they tend to conform with the majority of the members in their social networks. The covariation of group members' consumption is significantly more prevalent for temptation goods than for non-temptation

[28] Some households have negative income, so it is not clear whether simply using income minus consumption would yield meaningful results.

goods. In addition, results differ depending on how observable the goods are—public alcohol consumption exhibits stronger peer pressure than alcohol consumption at home. In conclusion, social norm theory provides an essential and previously overlooked supplement to explain myopic consumption behaviors.

These results raise concerns about group-based financial products in which policymakers use peer pressure to encourage loan repayment and saving commitment. Peer effects may have undesirable consequences for these products. Socializing with peers who engage in undesirable financial behavior can make individuals behave more myopically by consuming more temptation goods, saving less money than they desire, and missing profitable investment opportunities. These outcomes may have particularly negative consequences for vulnerable households. While these group-based microfinance innovations have significant merits, financial institutions should require institutional monitoring of group dynamics and the effects of these dynamics on individual spending behaviors.

In addition, my results lend support to regressive sin taxes—taxing goods like cigarettes and alcohol more among the poor. Literature has brought up the possibility of regressive sin taxes as temptation goods are in general over-consumed disproportionately among low-income households (Allcott et al., 2018; Lockwood and Taubinsky, 2017). If there exhibit peer effects among such goods and even more so among the poor, we should impose more regressive sin taxes on goods that are consumed publicly. I am aware that this research is not a randomized control experiment. Nonetheless, my results provide an open discussion on further research to better understand the optimal regressive sin taxes, considering the potential over-consumption through network effects.

8 Mathematical Appendix

Prediction 1: *An increase in peers' temptation consumption will lead to an increase in individual i's temptation consumption as long as the behavior is observable* ($\frac{\partial z_{1i}}{\partial \overline{z_{1-ig}}} > 0$) *if* $\chi > 0$.

The main interest here is to analyze $\frac{\partial z_{1i}}{\partial \overline{z_{1-ig}}}$. Take partial derivative with respect to $\overline{z_{1-ig}}$ from equation 5:

$$\frac{\partial z_{1i}}{\partial \overline{z_{1-ig}}} + \frac{\theta_z}{\chi} e^{-\theta_z z_{1i}} \frac{\partial z_{1i}}{\partial \overline{z_{1-ig}}} = 1$$

$$\implies \frac{\partial z_{1i}}{\partial \overline{z_{1-ig}}} = \left[1 + \frac{\theta_z}{\chi} e^{-\theta_z z_{1i}}\right]^{-1}$$

As long as $\chi > 0$, $\frac{\partial z_{1i}}{\partial \overline{z_{1-ig}}} > 0$ ■

Prediction 3: *Peer effects on temptation consumption are stronger when peers' consumption behaviors are more observable* ($\frac{\partial^2 z_{1i}}{\partial \overline{z_{1-ig}} \partial \chi} > 0$).

Since we know that:

$$\frac{\partial z_{1i}}{\partial \overline{z_{1-ig}}} = \left[1 + \frac{\theta_z}{\chi} e^{-\theta_z z_{1i}}\right]^{-1}$$

So,

$$\frac{\partial^2 z_{1i}}{\partial \overline{z_{1-ig}} \partial \chi} = \left[1 + \frac{\theta_z}{\chi} (e)^{-\theta_z z_{1i}}\right]^{-2} \left[\frac{\theta_z}{\chi^2} (e)^{-\theta_z z_{1i}}\right]$$

This is positive because $\left[1 + \frac{\theta_z}{\chi} (e)^{-\theta_z z_{1i}}\right]^{-2} > 0$, and $\frac{\theta_z}{\chi^2} (e)^{-\theta_z z_{1i}} > 0$

The results are very similar in CRRA utility function: Assume $u(x) = \frac{x^{1-\gamma_x}}{1-\gamma_x}$ and $v(z) = \frac{z^{1-\gamma_z}}{1-\gamma_z}$. Equation 5 becomes

$$z_{1i} - \frac{1}{\chi}(z_{1i})^{-\gamma_z} = \overline{z_{1-ig}} - \frac{1}{\chi}(1+r)\delta(x_{2i})^{-\gamma_x}\left(1 - \frac{\partial z_{2i}}{\partial c_{2i}}\right) \tag{12}$$

Thus, as long as χ is greater than zero, the left-hand side of the equation is an increasing function in z_{1i}. Increasing peers' temptation consumption will lead to the increase of individual i's temptation consumption.

Prediction 4:
When individuals are poor, negative idiosyncratic shocks will increase total consumption ($\frac{\partial z_{1i}}{\partial \theta_{1i}} < 0$, and $\frac{\partial x_{1i}}{\partial \theta_{1i}} < 0$ as c is small);
If one poor peer encounters adverse shock, other things being equal, this negative peer's shock has a positive impact on temptation consumption.

From equation 3, we have:

$$v'(z_{1i}) = \chi(z_{1i} - \overline{z_{1-ig}}) + \delta u'(x_{2i}) \left(\frac{\partial x_{2i}}{\partial c_{2i}}\right)(1+r) \tag{13}$$

First, look at the right-hand side of equation 13. Higher θ_{1i} (positive income shock) will lead to smaller $u'(x_{2i})$, but larger $(1 - \frac{\partial z_{2i}}{\partial c_{2i}})$ (which is equal to $\frac{\partial x_{2i}}{\partial c_{2i}}$). These two countervailing effects result from the initial assumptions of the model: $u'(x_{2i})$ decreases along with the higher θ_{1i} because x_{2i} is a function of c_{2i}, where $c_{2i} = (1+r)(\theta_{1i}y_{1i} - x_{1i} - z_{1i}) + y_{2i}$. Because of the diminishing return of utility, $u'(x_{2i})$ will decrease when c_{2i} is higher. At the same time, this positive shock will increase $(1 - \frac{\partial z_{2i}}{\partial c_{2i}})$ because of the concave shape of temptation goods (i.e. $z''(c) < 0$). Thus, when the second effect dominates, the right-hand side of equation 3 will increase with respect to an increase in θ_{1i} For the left-hand side $(v'(z_{1i}))$ to increase, z_{1i} has to decrease. To conclude, $\frac{\partial z_{1i}}{\partial \theta_{1i}} < 0$ when c_{2i} is small.

To see why, among poorer individuals, the second effect $((1 - \frac{\partial z_{2i}}{\partial c_{2i}}))$ dominates the first $(u'(x_{2i}))$ on the right-hand side: $\frac{\partial z_{1i}}{\partial \theta_{1i}} < 0$ as long as $[u'(x_{2i})(1 - \frac{\partial z_{2i}}{\partial c_{2i}})]$ is an increasing function of c_{2i}. Suppose $\frac{\partial^2 z_{2i}}{\partial c_{2i}^2}$ is monotone, and $\frac{\partial^3 z_{2i}}{\partial c_{2i}^3} > 0$, there exists a sufficiently low c_{2i}, which makes $[u'(x_{2i})(1 - \frac{\partial z_{2i}}{\partial c_{2i}})]$ an increasing function in c_{2i}. Use the previous functional form to illustrate. $\frac{\partial z_{1i}}{\partial \theta_{1i}} = \frac{-(1+r)\delta}{\chi + \theta_z e^{-\theta_z z_{1i}}}(1+r)y_{1i}[-\theta_x e^{-\theta_x x_{2i}} - \frac{\partial^2 z_{2i}}{\partial c_{2i}^2}]$ Therefore, $\frac{\partial z_{1i}}{\partial \theta_{1i}} < 0$ when $-\theta_x e^{-\theta_x x_{2i}} - \frac{\partial^2 z_{2i}}{\partial c_{2i}^2} > 0$ (that said, $\frac{\partial^2 z_{2i}}{\partial c_{2i}^2} < -\theta_x e^{-\theta_x x_{2i}}$). Since $\frac{\partial^3 z_{2i}}{\partial c_{2i}^3} > 0$, $c < max\{\frac{\partial^2 z_{2i}}{\partial c_{2i}^2} + \theta_x e^{-\theta_x x_{2i}}\}$.

Similarly, from equation 4, we have:

$$u'(x_{1i}) = \delta u'(x_{2i}) \left(\frac{\partial x_{2i}}{\partial c_{2i}}\right)(1+r) = 0 \tag{14}$$

Positive income shock will lead to smaller $u'(x_{2i})$, and larger $(1 - \frac{\partial z_{2i}}{\partial c_{2i}})$ $(= \frac{\partial x_{2i}}{\partial c_{2i}})$. The left-hand side of equation 14 will increase when the positive shock leads to a much larger $(1 - \frac{\partial z_{2i}}{\partial c_{2i}})$. Similar conclusion can be achieved for x good: $\frac{\partial x_{1i}}{\partial \theta_{1i}} < 0$ when c_{2i} is small.

Following the same logic, a poor enough peer can also increase his temptation consumption when encountering negative income shock. Here I want to show the intuition that a poor peers' negative shock can lead to an increase in household's own temptation consumption if

holding all other peers' shock constant. Suppose that there is a household $j' \in \{$ poor & i's peer group $\}$, who encounters negative income shock (smaller $\theta_{1j'}$). Household j' will increase temptation consumption (i.e. $\frac{\partial z_{1j'}}{\partial \theta_{1j'}} < 0$) because the second effect $(1 - \frac{\partial z_{2j'}}{\partial c_{2j'}})$ dominates the first $(u'(x_{2j'}))$ on the right-hand side of equation 14. An increase in $z_{1j'}$ responding to a smaller $\theta_{1j'}$ will lead to an increase in the peers' average temptation consumption $(\overline{z_{1-ig}})$ because $j' \in \{$ i's peer group $\}$. Based on prediction 1, an increase in peers' average temptation consumption will result in an increase in individual's own temptation consumption. Similar logic applies if more than one poor peers encounter negative shock event.

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Figure 3: Concavity of Temptation Consumption

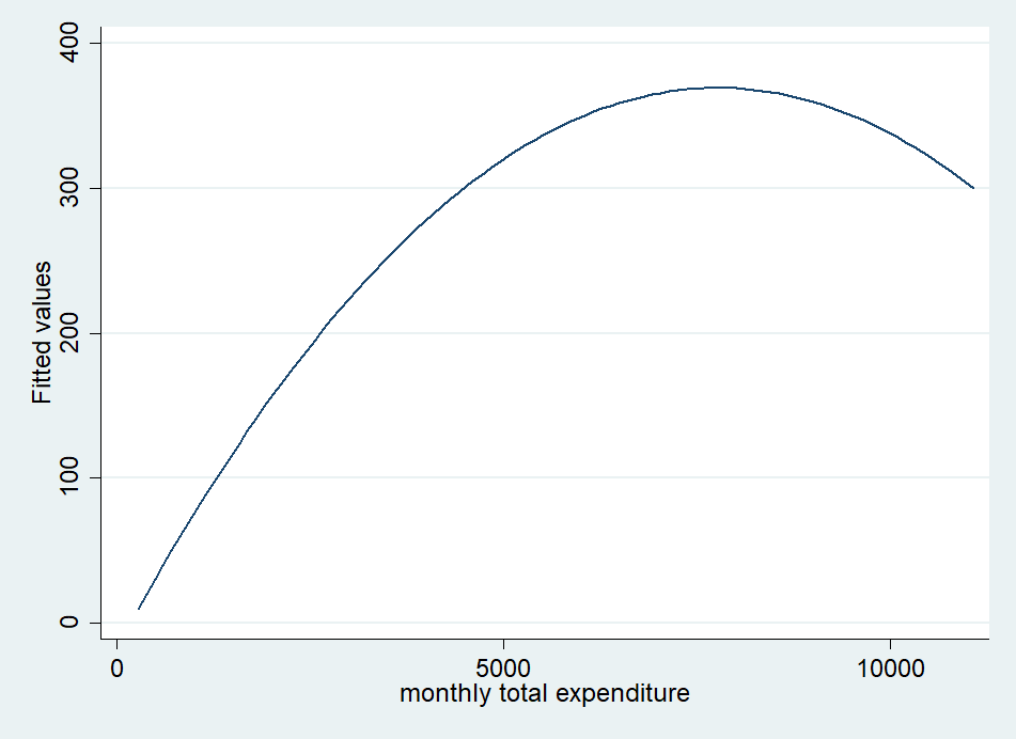

Table 1: Predictions from Social Norm and Risk-sharing Model

	Specification	Social Norm	Risk-sharing
1: Own and peer	$temp_{it} = \alpha_1 temp_{G_{it}} + controls + \varepsilon_{it}$	$\alpha_1 > 0$	$\alpha_1 > 0$
2: Extra Control	$temp_{ivt} = \gamma_1 temp_{G_ivt} + \gamma_2 cons_{G_ivt} + controls + \varepsilon_{ivt}$	$\gamma_1 > 0$	$\gamma_1 = 0$, $\gamma_2 > 0$
3: Non-temp vs temp	$temp_{ivt} = \gamma_{temp} temp_{G_ivt} + controls + \varepsilon_{ivt}$ $nontemp_{ivt} = \gamma_{nontemp} nontemp_{G_ivt} + controls + \xi_{ivt}$	$\gamma_{temp} > \gamma_{nontemp}$	$\gamma_{temp} = \gamma_{nontemp}$
4: Observability	$alcoholTOTAL_{ivt} = \gamma_{temp_H} alcoholHOME_{G_ivt} + controls + \varepsilon^H_{ivt}$ $alcoholTOTAL_{ivt} = \gamma_{temp_O} alcoholOUT_{G_ivt} + controls + \varepsilon^O_{ivt}$	$\gamma_{temp_O} > \gamma_{temp_H}$	$\gamma_{temp_O} = \gamma_{nontemp_H}$
5: Shock event	$temp_{ivt} = \beta_{temp1} healthshock_{G_ivt} + \beta_{temp2} healthshock_{ivt} +$ $controls + \epsilon^{temp}_{ivt}$ $nontemp_{ivt} = b_{nontemp1} healthshock_{G_ivt} + b_{nontemp2} healthshock_{ivt}$ $+controls + \epsilon^{nontemp}_{ivt}$	$\beta_{temp1} > 0$, $\beta_{temp2} > 0$ $b_{nontemp2} > 0$	$\beta_{temp1} < 0$, $\beta_{temp2} = 0$; $b_{nontemp1} < 0$ $b_{nontemp2} = 0$

Table 2: Summary Statistics

	mean	sd	min	max	N
Temptation consumption	94	211.9145	0	7433	26928
Non temptation consumption	1,393	3482.114	37	287815	26928
Total consumption	1,487	3528.544	37	287815	26928
Alcohol consumption at home	31	158.2397	0	6687	26928
Alcohol consumption outside	12	51.46327	0	1680	26928
Sickness	6.36	15.52159	0	686	26928
Temptation spending among total consumption	0.068	0.081228	0	0.7208	26928
Household per-capita monthly income	2,872	11765.49	-301900	430397	26928
Household Size	4.37	1.9368	1	15	26928

Note: All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000)

Figure 4: Histogram of Proportional Spending on Temptation Goods

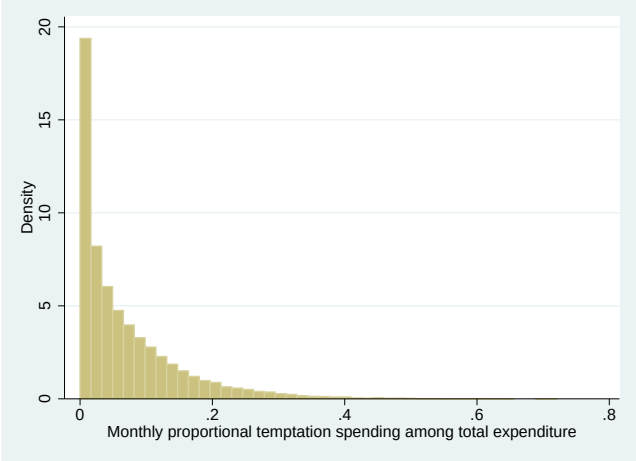

Table 3: Correlation of Social Network

Income	0.1470***
Household size	0.1342***
Percentage of ag income (differed by year)	0.5286***
Percentage of ag income (average throughout years)	0.3802***
Days of health shock	0.0207***

*** p<0.01, ** p<0.05, * p<0.1

Table 4: Consumption Relationship between Own and Peer

	temp	non-temp	temp	non-temp	temp
	OLS			IV	
	(1)	(2)	(3)	(4)	(5)
Peer's temptation consumption	0.0439**		1.516*		1.636*
	(0.0158)		(0.784)		(0.883)
	[0.005]***		[0.0000]***		[0,0000]***
Peer's non-temptation consumption		0.0190		1.153	
		(0.0128)		(0.812)	
		[0.1178]		[0.0599]*	
Household size	-10.86***	-136.2**	-10.63***	-140.8**	-10.57***
	(3.031)	(47.53)	(3.276)	(61.27)	(3.211)
	[0.002]***	[0.004]***	[0.004]***	[0.012]**	[0.004]
Village-year fixed effect	Yes	Yes	Yes	Yes	Yes
Seasonal fixed effect	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes
Controlling for peer's total consumption	No	No	No	No	Yes
Observations	26,928	26,928	24,353	24,353	24,353
F-stat of 1st Stage			7.206	2.874	6.423
CI of IV coefficient using CLR			[.4682, 5.9437]		[.4980, 7.5359]

Robust standard errors clustered at the village level in parenthesis; p value using wild cluster bootstrap reported underneath the robust standard errors

*** p<0.01, ** p<0.05, * p<0.1

All dependent variables are the level of household's per capita monthly consumption. Peer's consumption is calculated as the average level of per capita consumption excluding own household's consumption. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i. Conditional Likelihood Ratio (CLR) Test is developed by Moreira (2002). Similar to Anderson-Rubin (AR) test, CLR test gives robust confidence set under weak instruments. Yet, CLR test outperform AR test in power simulations (Andrews et al 2006).

Table 5: Alcohol Consumption at Home and Outside

	Dependent Variable: Household's alcohol consumption							
	Total				At home		Total	
	OLS	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer's alcohol consumption at home	0.00239		3.098		2.406		3.602	
	(0.00747)		(4.524)		(3.570)		(5.978)	
	[0.7342]		[0.5039]		[0.5108]		[0.5558]	
Peer's alcohol consumption outside		0.193**		4.316***		2.169*		4.317***
		(0.0839)		(1.472)		(1.223)		(1.474)
		[0.0394]**		[0.0103]**		[0.0963]*		[0.0103]**
Peer's total consumption							-0.0293	-0.000110
							(0.0553)	(0.000561)
							[0.6048]	[0.8470]
Household size	-6.166***	-6.197***	-4.738	-8.797***	-2.807	-5.431**	-4.334	-8.798***
	(1.924)	(1.932)	(5.201)	(3.049)	(3.775)	(2.421)	(6.071)	(3.049)
	[0.0281]**	[0.0268]**	[0.3766]	[0.0113]**	[0.4687]	[0.0403]**	[0.4862]	[0.0039]***
Village-year fixed effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	26,928	26,928	24,353	24,353	24,353	24,353	24,353	24,353
F-stat of 1st Stage			2.345	21.52	2.345	21.52	2.064	21.47

Robust standard errors clustered at the village level in parenthesis; p value using wild cluster bootstrap reported underneath the robust standard errors

*** p<0.01, ** p<0.05, * p<0.1

Peer's consumption is calculated as the average level of per capita monthly consumption excluding own household's consumption. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i.

Table 6: Shock on Consumption Pattern with Income Interaction

	temp OLS (1)	non-temp OLS (2)	temp IV (3)	non-temp IV (4)	temp IV (5)	non-temp IV (6)
Poor peer's total days of health shock	0.0272	0.155	1.223***	-7.188	1.172***	-7.088
	(0.0505)	(0.330)	(0.347)	(10.19)	(0.313)	(10.00)
	[0.5980]	[0.6451]	[0.0062]***	[0.4729]	[0.0025]***	[0.4787]
Individual's days of health shock	-0.117	5.030	-0.175	5.388	-0.182	5.401
	(0.230)	(3.291)	(0.238)	(3.292)	(0.237)	(3.302)
	[0.6187]	[0.14725]	[0.3446]	[0.1715]	[0.3321]	[0.1717]
Poverty	-83.78***	-1,204***	-85.09***	-1,196***	-83.17***	-1,200***
	(11.07)	(90.62)	(10.61)	(85.59)	(10.53)	(88.42)
	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***	[0.0000]***
Poverty*individual's health shock	0.0572	-6.208*	0.0925	-6.425**	0.0946	-6.429**
	(0.228)	(3.169)	(0.246)	(3.071)	(0.244)	(3.070)
	[0.8050]	[0.0689]*	[0.5934]	[0.0955]*	[0.6227]	[0.0955]*
Household size	-6.593*	-78.73	-6.298**	-80.54*	-6.412**	-80.32*
	(3.130)	(45.56)	(3.165)	(43.44)	(3.115)	(43.60)
	[0.0524]	[0.1045]	[0.0665]	[0.0171]	[0.0632]*	[0.0173]**
Village-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Additional control for # of poor peers					Yes	Yes
Observations	28,008	28,008	28,008	28,008	28,008	28,008
F-stat of 1st Stage			114.8	114.8	125.7	125.7

Robust standard errors clustered at the village level in parenthesis; p value using wild cluster bootstrap reported underneath the robust standard errors

*** p<0.01, ** p<0.05, * p<0.1

Peer's consumption is calculated as the average level of per capita monthly consumption excluding own household's consumption. Peer's health shock is instrumented using contemporaneous shock information of individual i's friends of friends who are not directly linked with i.

9 Appendix

Table A-1: Risk-sharing at the Village

	Household's consumption per capita	
	level	first difference
Net income per capita	0.0300***	
	(0.00340)	
Net income per capita (first difference)		0.0237
		(0.0230)
Observations	3,804	3,170
R-squared	0.095	0.033

Standard errors in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

All dependent variables are at the level of household's per capita yearly consumption.

People within the same village are categorized as in the same social network.

Table A-2: Consumption Relationship between Own and Peer (Different Time Frame)

	temp	non-temp	temp	non-temp
		IV		
		t-2 instrument on t-1		
	(1)	(2)	(3)	(4)
Peer's temptation consumption at $t-1$	1.154*		1.264	
	(0.695)		(0.822)	
Peer's non-temptation consumption at $t-1$		1.146		-45.52
		(0.726)		(30.70)
Peer's consumption at $t-1$			-0.0121	45.10
			(0.0127)	(30.38)
Household size	-12.37***	-146.3**	-12.40***	-186.1**
	(4.003)	(60.25)	(4.041)	(66.29)
Village-year fixed effect	Yes	Yes	Yes	Yes
Seasonal fixed effect	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Observations	24,010	24,010	24,010	24,010
F-stat of 1st Stage	7.549	3.350	6.598	1.026

Robust standard errors clustered at the village level in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

All dependent variables are at the level of household's per capita monthly consumption. Peer's consumption is calculated as the average level of per capita monthly consumption excluding own household's consumption. In columns (1) to (4), peer's t-1 consumption is instrumented using 2-period lagged consumption of individual i's friends of friends who are not directly linked with i.

Table A-3: Alcohol Consumption at Home and Outside (Different Time Frame)

	Dependent Variable: Household's alcohol consumption					
	Total		At home		Total	
			IV			
			$t-2$ instrument on $t-1$			
	(1)	(2)	(3)	(4)	(5)	(6)
Peer's alcohol consumption at home at $t-1$	1.263		0.339		1.563	
	(1.955)		(1.005)		(2.850)	
Peer's alcohol consumption outside at $t-1$		4.684**		2.262		4.698**
		(2.054)		(1.628)		(2.063)
Peer's total consumption at $t-1$					-7.513**	-8.378***
					(3.187)	(3.235)
Household size	-7.483**	-8.378***	-4.694**	-5.244**	-7.484**	-8.377***
	(2.990)	(3.234)	(2.236)	(2.565)	(2.971)	(3.236)
Village-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	24,010	24,010	24,010	24,010	24,010	24,010
F-stat of 1st Stage	0.530	19.57	0.530	19.57	0.365	19.50

Robust standard errors clustered at the village level in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

Peer's consumption is calculated as the average level of per capita monthly consumption excluding own household's consumption. Peer's t-1 consumption is instrumented using 2-period lagged consumption of individual i's friends of friends who are not directly linked with i.

Table A-4: Consumption Relationship between Own and Peer (Sub-sample)

	temp OLS (1)	non-temp OLS (2)	temp IV (3)	non-temp IV (4)	temp IV (5)	non-temp IV (6)
Peer's temptation consumption	0.0117		1.339**		1.356**	
	(0.0177)		(0.639)		(0.644)	
Peer's non-temptation consumption		-0.0120***		-1.082		-55.65
		(0.00247)		(1.244)		(51.32)
Peer's consumption					-0.00487	55.44
					(0.00477)	(51.16)
Household size	-11.35**	-111.3	-7.904	-42.40	-7.798	-37.67
	(4.078)	(78.22)	(4.885)	(96.05)	(4.806)	(184.0)
	(3.031)	(47.53)	(3.276)	(61.27)	(3.211)	(53.10)
Village-year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,304	11,304	8,946	8,946	8,946	8,946
F-stat of 1st Stage			10.36	3.007	10.21	1.040

Robust standard errors clustered at the village level in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

All dependent variables are at the level of household's per capita monthly consumption. Peer's consumption is calculated as the average level of per capita monthly consumption excluding own household's consumption. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i

Table A-5: Alcohol Consumption at Home and Outside (Sub-sample)

	Dependent Variable: Household's alcohol consumption							
	Total				At home		Total	
	OLS	OLS	IV	IV	IV	IV	IV	IV
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Peer's alcohol consumption at home	0.00364		2.297***		1.889***		2.332***	
	(0.0138)		(0.799)		(0.665)		(0.830)	
Peer's alcohol consumption outside		-0.0155		3.187***		1.178**		3.163***
		(0.0409)		(0.677)		(0.505)		(0.685)
Peer's total consumption							-0.00809	0.000513***
							(0.00787)	(0.000178)
Household size	-7.060***	-7.077***	-7.740***	-3.822	-5.985**	-3.875	-7.599***	-3.850
	(2.299)	(2.314)	(2.636)	(2.988)	(2.575)	(2.837)	(2.450)	(2.992)
Village-year fixed effect		Yes	Yes	Yes	Yes	Yes	Yes	Yes
Seasonal fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	11,304	11,304	8,946	8,946	8,946	8,946	8,946	8,946
F-stat of 1st Stage			1.745	36.79	1.745	36.79	1.720	37.19

Robust standard errors clustered at the village level in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

Peer's consumption is calculated as the average level of per capita monthly consumption excluding own household's consumption. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i.

Table A-6: Shock on Consumption Pattern with Income Interaction (Sub-sample)

	temp	non-temp	temp	non-temp
	OLS		IV	
	(1)	(2)	(3)	(4)
Log peer's days of health shock	-3.961	-21.58	104.3	-568.2
	(2.787)	(31.89)	(123.9)	(545.0)
Log individual's helth shock	4.431	180.9	10.52	224.7*
	(6.059)	(107.1)	(10.06)	(131.6)
Log net income	3.485***	24.08	4.005***	12.87
	(0.975)	(17.27)	(1.549)	(20.26)
log (Income)*log (individual's helth shock)	-0.529	-24.70	-1.052	-31.09
	(0.654)	(15.49)	(1.004)	(18.95)
Household size	-14.13**	-117.8	-11.47	-67.42
	(5.936)	(123.4)	(7.435)	(131.5)
Village-year fixed effect	Yes	Yes	Yes	Yes
Seasonal fixed effect	Yes	Yes	Yes	Yes
Household fixed effect	Yes	Yes	Yes	Yes
Observations	7,284	7,284	5,654	5,654
F-stat of 1st Stage			24.75	24.75

Robust standard errors clustered at the village level in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

Peer's consumption is calculated as the average level of per capita monthly consumption excluding own household's consumption. Peer's health shock is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i.

Table A-7: Temptation Consumption excluding Alcohol Consumption

Dependent variable: household's temptation consumption excluding alcohol consumption		
	(1)	(2)
Peer's temptation consumption (except alcohol)	1.635*	1.652
	(0.992)	(1.009)
	[0.41916]	[0.37924]
Peer's total consumption		-0.00154
		-0.00113
		[0.19162]
Household size	-4.128**	-4.124**
	(1.638)	(1.657)
	[0.01597]**	[0.02794]**
Village-year fixed effect	Yes	Yes
Seasonal fixed effect	Yes	Yes
Household fixed effect	Yes	Yes
Observations	24,353	24,353
F-stat of 1st Stage	28.54	27.97

Robust standard errors clustered at the village level in parenthesis; p value using wild cluster bootstrap reported underneath the robust standard errors

*** p<0.01, ** p<0.05, * p<0.1

All dependent variables are at the level of household's per capita monthly consumption. Peer's consumption is calculated as the average level of per capita monthly consumption excluding own household's consumption. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i. The social network is defined using people's financial, gift-giving, and labor-sharing relations.

Table A-8: Peers' Temptation on Saving

Dependent variable: Whether household opens a saving account in the given month	
Peer's temptation consumption	-0.00224
	(0.00197)
Household size	0.0135*
	(0.00724)
Village-year fixed effect	Yes
Seasonal fixed effect	Yes
Household fixed effect	Yes
Observations	24,346
F-stat of 1st Stage	6.84
CI of IV coefficient using CLR	[-.0093, -.0009]

Robust standard errors clustered at the village level in parenthesis

*** p<0.01, ** p<0.05, * p<0.1

Saving captures whether any household member has opened saving account in the past month. Peer's consumption is calculated as the average level of per capita monthly consumption excluding own household's consumption. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i. The social network is defined using people's financial, gift-giving, and labor-sharing relations. Conditional Likelihood Ratio (CLR) Test is developed by Moreira (2002). Similar to Anderson-Rubin (AR) test, CLR test gives robust confidence set under weak instruments. Yet, CLR test outperform AR test in power simulations (Andrews et al 2006).