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

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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.

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1 Introduction

Current literature in development economics highlights 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 the financial context, individuals may overborrow when they do not recognize their preferences for immediate payoffs (Heidhues and Kőszegi, 2010). Crop farmers may struggle to save small amounts of money for later use on fertilizers, leading to suboptimal crop yields (Banerjee and Duflo, 2007). Low-income households often devote a significant portion of their disposable income to 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 as an individual's problem. I incorporate peer effects into our understanding of the myopic behaviors of the poor, especially focusing on 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 incorporating peer effects into the temptation model developed by Banerjee

[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)

and Mullainathan (2010). I define temptation goods as alcohol, tobacco, and gambling, because these goods can further illustrate the potential negative consequences of 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. Thus, they 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 the unobservable correlated shocks and omitted covariates. For example, households in the same village or joining the same organization may suffer from the same unobservable shocks that drive their consumption behaviors. Lastly, people select their own peers, making the network definition endogenous.

To address the identification challenges, I apply an instrumental variable approach. This approach identifies 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 assumption of exclusion restriction is based on the premise that

[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, these 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.

the excluded peers do not directly interact with the focal individuals. This is evident as there are no actual labor-sharing, gift-giving, or financial transaction relations documented throughout the entire 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 correlated effects and unobservable common shocks. The lagged consumption variables prevent the problem of reverse causation or joint consumption decision.

Overall, this study demonstrates that households' temptation consumption, particularly of observable goods, is considerably influenced by peer effects. A one bhat increase in peers' average temptation consumption leads to a 1.5 bhat increase in an individual's temptation consumption, at a significance level of 10%. This translates to an increase of roughly one standard deviations in response to a one standard deviation increase in peers' temptation consumption. Although this magnitude appears larger than that found in another developing country, India, this difference may be due to the fact that I primarily measure temptation consumption, which is more susceptible to the sway of peers' consumption compared to non-temptation consumption (Roychowdhury, 2019). It is crucial to remember, however, that the temptation consumption measure in this study include elements of both observable and less observable items, each of which may exhibit distinct relationships with peer effects. As a result, interpretation of the translated magnitude requires caution, with due attention paid to the nuanced implication of our proposed mechanism. Besides, stronger peer effects in developing countries have been commonly observed in the literature.[5]

Furthermore, the findings suggest that poorer households consume a higher share of their temptation goods per marginal dollar than rich households, reflecting the concave shape of temptation consumption. This finding confirms the theoretical assertion that cognitive constraints are more pronounced among poor households (Chemin et al., 2013; Mani et al., 2013). Additionally, robustness tests reveal that social norms play a more significant role in guiding temptation consumption decisions than risk-sharing does. In summary, these results underscore the importance of peer behavior in modeling myopic consumption behaviors.

My study contributes to the current literature in several ways. First, it enriches 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

[5]Both my study and Roychowdhury (2019) report larger magnitudes than those found in De Giorgi et al. (2020)'s research.

using relatively long-term high-frequency consumption data.[6] Battaglini et al. (2005) is the only theoretical paper that models peers' influence on individuals' self-control problem.[7] Few empirical studies directly test peer effects on self-control, and all of them focus on student populations in developed countries. For example, Battaglini et al. (2017) uses data from the National Longitudinal Survey of Adolescent to Adult Health (Add Health) to understand the self-control levels of high school students within peer groups. Limited by the data, they use a single 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 finds that students who are more connected have more self-control. The current empirical literature is 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 join a social group. This assumption may not hold true in my context. In rural Thailand, peers may not correlate 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 insight and empirical evidence based on a relatively long-term monthly consumption data.

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[8]. Others also find a social influence on households' consumption choice based on different reference group definition such as, postcodes in the Netherlands (Kuhn et al., 2011), counties

[6]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.

[7]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.

[8]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)

in the UK (Quintana-Domeque and Wohlfart, 2016), and city in the U.S. (Ravina, 2005). De Giorgi et al. (2020) uses the so-called distance-3 peer—co-workers' spouses' co-workers—to instrument peer effects on household consumption from Danish's tax record data. My analysis aims to understand a broader population in a developing country, potentially providing insights for poverty reduction policies. As people do not form social ties simply based on geographic or racial boundaries, my network data can effectively capture social relations beyond the natural physical boundaries utilizing long-term real-world transactions.

Third, this paper contributes to the literature on psychology and poverty. Emerging research indicates that poverty can lead to a reduction in cognitive resources, resulting in 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, particularly those highly dependent on agriculture. Mani et al. (2013) find that poor farmers' cognitive function declines before the harvest cycle compared to the same farmers post-harvest when they are richer. This decline occurs because poor farmers' mental resources are preoccupied with poverty-related concerns. Shah et al. (2012) also demonstrate, through various experiments, that scarcity can consume mental resources. In this paper, I find that poor households' facing negative income shocks exhibit more severe temptation consumption behaviors, potentially driven by their cognitive distress.

Finally, in terms of policy implications, my findings enhance our understanding of consumption behaviors among the poor and suggest policy applications for future financial instruments. Recent financial innovations in the microfinance industry attempt to tackle the self-control problem. One example is a "commitment saving device," which has been shown to help myopic people save more (Ashraf et al., 2006). Another example is the establishment of local saving groups (e.g., self-help group[9] 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 repayment issues in microfinance, because these effects may entail unintended consequences. Socializing with myopic peers can lead an individual to allocate their financial resources in a more myopic manner.

[9]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 Social Norm Model

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

2.1 Household Maximization Problem

The basic setup follows the model created by Banerjee and Mullainathan (2010). This model provides insights into self-control problems through goods-specific preferences, and yields similar predictions to a hyperbolic discounting model. Household i maximizes a utility function that depends on two types of separable consumption: temptation goods (z_i) and goods without temptation (x_i). Temptation goods, such as alcohol and tobacco, provide utility only at the point of consumption, leading to present biased behavior. This feature yields goods-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), who found through a randomized control experiment in India that low-income groups exhibit a high demand for commitment to sobriety.[10]

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 1 that temptation

[10]The alternative way to model those goods is a rational addiction model (Becker and Murphy, 1988). In this model, the goods can be considered addictive if past consumption of the good increases the marginal utility of current consumption. However, Schilbach (2019)'s recent research published in the American Economic Review found that, empirically, a self-control model better predicts low income people's alcohol consumption behavior. Their empirical evidence indicates that drivers exhibit a demand for commitment to sobriety, which contrasts with the rational addiction model. It is important to note that, while some goods may still be addictive (e.g. tobacco and other drugs), my analysis does not take into account the usage of these goods due to limitations in the survey data. In addition, it is plausible that consumption behavior varies among people who attempt to quit versus those who do not, with some exhibiting greater sophistication in their demand for commitment to quit temptation consumption. While my data cannot distinguish between people with different levels of sophistication, I acknowledge that this heterogeneity may lead to different model predictions. However, since my analysis focuses on estimating peer effects on temptation consumption, I do not explicitly model the heterogeneity of people's sophistication.

increases with consumption at a decreasing rate. This assumption implies different levels of myopia for the rich and the poor—the poor behave as if they were more myopic than the rich.[11] 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 consumed in the first period, but gets discounted utility from only x goods consumed in the second period. This setup fits the property of the temptation goods, which households cannot resist "now," but 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 gaining utility from consumption, individuals also care about how they appear within their social group and may conform to the behavior of the majority to gain social rewards. The deviation function, denoted as $\Phi(.)$, captures the payoff from deviating from the behavior of the majority, which can be seen as a "social norm." The idea is similar to the literature modeling consumption externalities, which makes own consumption dependent upon the reference group's consumption (Alvarez-Cuadrado et al., 2016; Drechsel-Grau and Schmid, 2014; Maurer and Meier, 2008; Quintana-Domeque and Wohlfart, 2016). However, this study takes a different approach to focus on peer effects on temptation consumption, also known as "keeping up with the Joneses" behavior. The functional form of this peer consumption externalities varies, but the idea here only captures the partial equilibrium effect without imposing strategic behaviors between one's own and the referenced group. The parameter χ in the social norm function reflects the salience or observability of the behavior, and is analogous to the concept of social signaling in other studies, such as Bénabou and Tirole (2006)'s paper, which measures the visibility or probability of an action being observed by others. For instance, individuals may be concerned about deviating from their peers, and the extent of this concern may depend on how much others know about it.

Therefore, household i in a social network group g has the following maximization prob-

[11] I did not use the standard hyperbolic discounting model, or Battaglini et al.'s (2005) self-control model due to the lack of direct behavioral vairbles needed for empirical test. While Battaglini et al.'s model is theoretically useful, there is no enough information in the data to conduct empirical tests based on this model. In addition, based on my fieldwork experience, the temptation framework is more reflective of reality and can be viewed as an extreme version of hyperbolic preferences over temptation goods.

lem:

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

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 increases, the marginal utility from temptation goods decreases much faster for temptation goods than non-temptation goods. 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 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 a

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

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

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 9 Mathematical Appendix.

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. To illustrate, imagine a household where the members are trying to cut down on their alcohol consumption. If their peers continue to drink alcohol frequently, the household may be more likely to also give in to temptation and consume alcohol, even if they had previously intended not to.

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

This prediction suggests that households are more likely to be influenced by their peers' temptation consumption than their non-temptation consumption. The intuition behind this prediction is that people are more likely to conform to their peers' behavior when it comes to temptation goods, as they are often associated with immediate gratification and impulsive behavior. On the other hand, non-temptation goods are less likely to trigger impulsive behavior, so households are less likely to be influenced by their peers' consumption of these goods.

To test this prediction, I will assume that peers' consumption of temptation goods ($\overline{z_{1-ig}}$) and non-temptation goods ($\overline{x_{1-ig}}$) are exogenous, and estimate the effect of these variables on household i's consumption of temptation and non-temptation goods, respectively.

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. To illustrate, consider different types of consumption where some are more visible, such as consuming alcohol in public, and some are less visible, such as consuming at home. The model predicts that more observable consumption would be subject to stronger peer effects. This is because individuals are more likely to conform to social norms when their behavior is more visible to others.

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 an adverse shock, other things being equal, this negative peer's shock will have a positive impact on temptation consumption.[12]

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

[12]The specific assumption leading to his intuition can be shown, but the aggregate effect of peers' shock cannot be generally proved.

in the mathematical appendix in Section 9.

To illustrate the intuition behind, imagine a household that is already struggling to make ends meet. A negative income shock, such as the loss of a job or unexpected medical expenses, would increase the psychological and financial stress on the household, making it more difficult to resist temptation and leading to an increase in the consumption of temptation goods. Similarly, if one poor peer in a social group experiences a negative income shock, their increased consumption of temptation goods may directly influence the average peers' temptation consumption. This will further increase individual's consumption of temptation goods, in accordance with Prediction 1. This is supported by a body of research that has found poverty and scarcity to be associated with higher stress levels and worse cognitive performance (Chemin et al., 2013; Haushofer, 2011; Haushofer et al., 2011; Mani et al., 2013; Shah et al., 2012).

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

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.

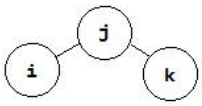
In the peer effect literature, α_1 is the endogenous peer effects (i.e. the effect of the peer group's mean outcome), and α_2 captures the contextual effects (i.e. the effect of the peer group's mean characteristics). The key task is to identify the endogenous peer effect. The literature has recognized 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), occurs 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 my 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.

Since in my analysis each household has different peer groups and groups mostly have

Figure 1: Network illustration



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).[13]

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).[14] After controlling for household fixed effects, there is still a concern about 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 ceremonies or holidays, such as the Lunar New Year in Thailand. In addition, one can envision some common village-level economic shocks influencing temptation consumption patterns, as people might drink more during a good harvest. Moreover, the Thai government has implemented various financial inclusion policies

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

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

that can impact the operations and outcomes of different financial institutions across villages. To address these confounding factors, I control for village-year fixed effects and seasonal effects in the analysis.

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).[15] 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 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

[15] In Quintana-Domeque and Wohlfart (2016), they claimed that "*I 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.

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.[16] 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 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, I estimate a standard 2SLS approach. The first-stage regression for the peer group is:

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

[16] Although one could imagine that if someone was sick last month, people might stop inviting them to parties to drink together, leading to attenuated peer effects. This is not what I find. I discover that shocks translate into more temptation consumption, and also translate into peer effects on temptation. So if this were to happen, this concern would only make my results stronger.

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

The theory generates several predictions, including the prediction on δ_1, which is reiterated in this section. All the regressions use a similar instrumental technique.

Peer effects on temptation: One key prediction of the model is that a household's own temptation consumption is influenced by the temptation consumption of their peers, as indicated by Prediction 1 ($\delta_1 > 0$ in equation 9). This peer effect should hold even after controlling for peers' total consumption, which helps distinguish it from the alternative mechanism of risk sharing, whose predictions are presented in Section 6.1. 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 a 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 the social

norms mechanism (i.e. $\beta_{temp1} > 0$):

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

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). However, 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.

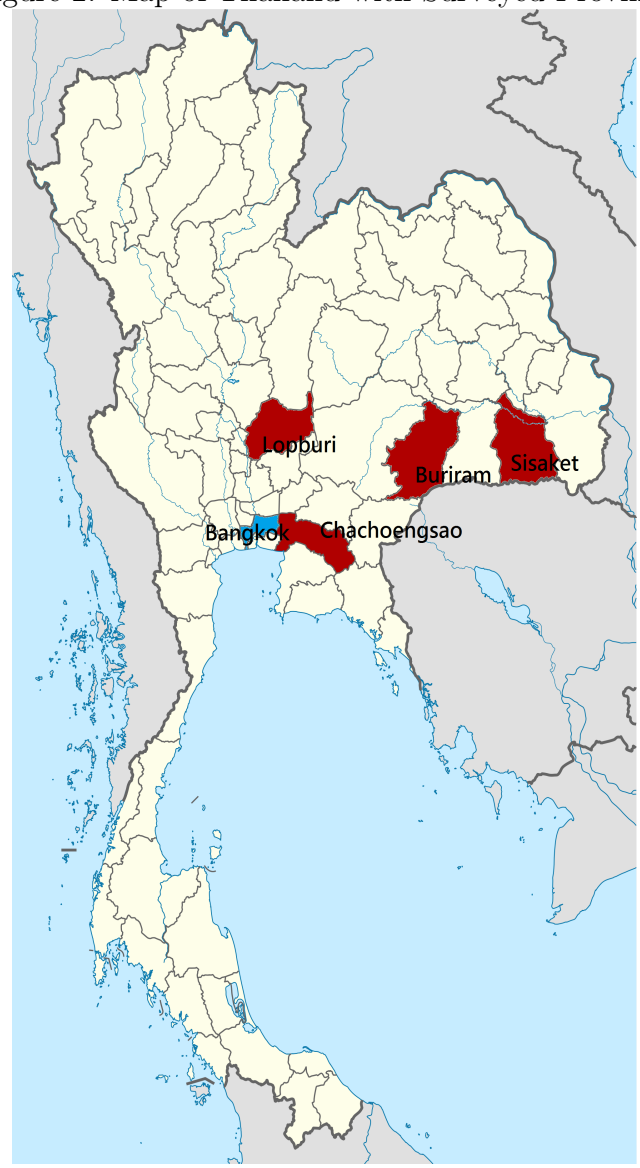
4 Data

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. The more detailed explanation of the sampling structure can be found from Binford et al. (2004). This survey has been used in several published papers on other topics, with additional details provided in Felkner et al. (2009) and Pawasutipaisit and Townsend (2011).

The data include households' demographic characteristics, expenditure, income, along

Figure 2: Map of Thailand with Surveyed Provinces



with detailed information on financial, gift exchange, and labor-sharing relationships. These transactional relationships are time-varying. The monthly temporal scale (some are in weekly basis) proves valuable for the dataset, as the expenditure information is notoriously difficult to recall, and frequent data collection mitigates potential measurement error. In addition, the breadth of the expenditure information is notably comprehensive, covering categories such as various food items, oil and fat, sugar and sweet, beverages, and even often-overlooked categories such as alcohol and gambling. These traditionally elusive forms of consumption are recorded due to the diligent work of the team, their established trust within the community,

and their robust logistical arrangements. To the best of my knowledge, this dataset presents the most comprehensive consumption information, facilitating the segregation of expenditure into temptation and non-temptation categories. The transactional relationships also enable a more nuanced representation of social ties within the village. Existing literature tends to generalize networks using the entire village as a unit; however, it is essential to recognize that not all households within a village maintain close friendships with one another. The subsequent section will discuss the more detailed definition of social networks in this specific context.

4.2 Social Network Data

I categorize household-level social networks, utilizing actual transactions such as borrowing and lending, gift-giving, and labor sharing over an extended period of time, rather than relying on hypothetical scenarios. By focusing on transaction relations, I capture individuals' true social networks, rather than relying on proxies. This concrete definition minimizes measurement errors without requiring households' subjective evaluations. Moreover, the rare survey design, involving repeated monthly observations, reduces recall errors and enhances the completeness of network data. This study extends beyond natural boundaries, such as neighbors, blood relations, or co-workers, capturing individuals with whom participants spend time through labor-sharing relationships and those with whom they engage in monetary transactions. Although people within the social network using my definition may still be subject to various common village factors which may confound with peer effects,[17] it is reassuring that this definition captures the underlying friendship relations, as gift-giving, borrowing, and labor sharing transactions are common among friends in Thai villages (Kinnan and Townsend, 2012). As noted in Kinnan and Townsend (2012), financial transfers and gift-giving in Thai villages are prevalent among family and friends. Furthermore, the survey data reveals that households exchange labor with their friends, neighbors, and relatives.

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

[17] Although individuals within the same social network may be influenced by shared environmental factors, such as village environment or local policies, I account for such factors using fixed effects models.

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.[18] 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 possible that i lies about his relationship with j.[19] 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.[20] 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.[21] 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 people are not friends at time t.[22] I consider this approach capturing the underlying peer networks people are embedded in.

[18] 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.

[19] 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.

[20] 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.

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

[22] 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 this present paper) 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, I may be overlooking silent links that do not get activated during the time of my study.*"

I list some other advantages of using this network data. First, the high-frequency collection of the data ensures that using the excluded network is a valid IV approach, where household i is only influenced by k through this common friend j's effect. Even though my network definition may still contain 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 about each other to exhibit a peer effect—the necessary exclusion restriction condition. Second, my network measure in the context of a developing country is 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 due to monetary or technological barriers. So the social relations captured within a village in my context are more complete than those in an urban developed world.[23]

4.3 Key Variables of Interest

The key outcome variable is the expenditure on temptation goods. To capture this type of consumption, I utilize the detailed monthly survey, which enables us to separate consumption into different categories. Specifically, I use household's expenditure on alcoholic beverages (at home), alcoholic beverages (consumed away from home), tobacco, lottery, and gambling to approximate households' temptation consumption.[24] It is worth noting that the survey only captures households' spending on various items. Since some of the expenditures may not result in immediate consumption, it is not possible for us to distinguish the precise timing of the consumption. I will use respondents' answers regarding their monthly expenditure as a proxy for households' monthly consumption[25]

The key explanatory variable is the consumption spending of the people within the net-

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

[24]Unfortunately, there may still be some important types of temptation consumption that are relevant but are not captured in the data. For example, drug use may be something that people are tempted to consume and may also be subject to peer effects. If I were able to capture this information in the analysis, I suspect that the peer effects on temptation consumption would be even stronger.

[25]Using spending as a proxy for consumption may cause overestimation because not all items purchased are consumed. However, it is plausible to assume that these expenditures are mostly consumed later on, especially since poor people are less likely to waste food. If these expenditures are indeed consumed later, there may be a delay before the peer effects become evident. My method of incorporating lagged variables in the estimation can reasonably address this factor. Furthermore, I also use different time lags as a robustness check (see Table B-2). Nonetheless, even though there may still be a discrepancy between actual spending and the amount consumed, the consistency of the estimates using lagged variables can reassure us that spending is a good proxy for consumption.

work. 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.

It is worth noting that all consumption variables are calculated on a per-capita basis. This definition, however, may underestimate the values of households' average per-capita consumption if it includes members who are children. Ideally, one could use a correction, such as the "OECD equivalence scale" to adjust for this. Unfortunately, due to Institutional Review Board restrictions, the Thai Townsend project team is unable to disclose comprehensive demographic details for all household rosters. Even though this definition may lead to underestimation for those consumption variables, as long as the composition of peers' consumption variation does not systematically correlate with an individual's consumption due to this household member composition issue, there may not be bias in my peer effect estimation. Additionally, given that my estimations rely on monthly fluctuations in peer consumption, the age composition of household members is not likely to exhibit systematic variation over this time period. This aspect can be largely addressed by the household fixed effects.

4.4 Summary Statistics

Table 3 presents the summary statistics derived from the Thai dataset. Notably, households spend a considerable portion of their budget to temptation goods, accounting for an average seven percent of total consumption. The annual expenditure on these goods is on par with the average yearly household spending on education.

Of the 480 total observations, 374 people can be linked with at least one peer within the same tambon, an administrative division larger than a village. On average, the network size is five, mostly neighbors and relatives.

Table 4 displays the basic correlations of characteristics between villagers and their peers. Individuals within the same network exhibits similarities in income levels, household sizes, and proportions of their agricultural income. The correlation concerning the percentage of agricultural income is particularly strong, suggesting that individuals tend to form networks with those engaged in the same occupation. This pattern may arise from labor-sharing

relationships, where individuals specialize in the same economic activity. When it comes to idiosyncratic health shocks, however, the correlation between peers' health shocks is notably weaker.

5 Empirical Results

The results using the instrumented social network information largely support the theory of social norms. In most instances, the instrument is valid, with high F-statistics in the first stage.[26] The results using instrumental variables are similar to those using OLS. Despite some missing observations when using the excluded network as instruments, the consistency in the results bolsters confidence in their validity.[27]

5.1 Peer Effects on Temptation and Non-temptation

Table 5 presents the OLS and IV results. The coefficient in column 3 of Table 5 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 even under weak instrument conditions. The findings remain robust, with the CLR test indicating positive confidence intervals.

The coefficients in the IV specification exceed those in the OLS coefficient. This means that the correlated effect (reflected in the disturbance term) that OLS coefficients capture actually opposes the direction of the peer effect. The larger IV is not unique to this study, as De Giorgi et al. (2010) also found this similar result. They explain that each unobservable common shock could possess a different sign, making OLS coefficients not unambiguously

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

[27]In order to use a friend of a friend as the instrument, there should exist such a 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.

larger than the IV estimators. In addition, due to the peer group not being perfectly overlapped, the simultaneity issue in the OLS case is significantly less compared to when using a fully overlapped social network definition.[28] Caeyers and Fafchamps (2015) further introduce the concept of "exclusion bias" to explain why OLS estimates of endogenous peer effects typically exceed their IV estimated counterparts. They illustrate that this bias naturally arises when researchers exclude an individual from their own peers, creating a downward bias in the OLS estimate as opposed to an upward bias. For example, if individual i possesses an ability higher than the average ability of its peers, excluding i will lower the average ability of i's peers, leading to a negative correlation between i's characteristics and the average characteristics of i's peers. Another potential reason for the larger IV estimators compared to OLS estimators could be the weak instrument used in this study. The diminished correlation between the instrumental and instrumented variables could inflate IV estimators. Columns 1 to 4 show that the coefficients of peers' temptation consumption exceed those of peers' non-temptation consumption. Given that the signs of the coefficients in both IV and OLS regressions align, these results lend support to the social norm mechanism that individuals experience disutility when their temptation consumption deviates from the average temptation consumption of their peers.

Columns 5 and 6 of Table 5 illustrate the consumption relationship between individuals and their peers, albeit with controls 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 comprehensive explanation of the prediction on the alternative risk-sharing mechanism is presented in Section 6.1). The outcomes offers additional evidence supporting the social norm mechanism: even when controlling for peers' total consumption, the peer effects on temptation consumption remain positive and significant. The coefficient on peers' temptation consumption is around 1.6, while the coefficient for peers' non-temptation consumption is much smaller and not statistically significant when controlling for peers' total consumption. All results in Table 5 are consistent with Predictions 1 and 2 under the social norm theory.

5.2 Observability

Table 6 presents peer effects of alcohol consumption at home versus alcohol consumption outside the home. The results support Prediction 3 in the social norm theory, which suggests

[28]For example, if a village is used as the social network definition, everyone's social network within the network group overlaps completely.

that peer effects are more significant in more observable consumption. Columns 1 to 4 display the effects of peers' alcohol consumption outside versus peers' alcohol consumption at home on a household's total alcohol consumption. Columns 1 and 2 present the results from the OLS specification, and columns 3 and 4 present the results from the IV specification. The findings indicate that the coefficients associated with peers' alcohol consumption outside the home are stronger than those associated with peers' alcohol consumption at home, which isconsistent with the social norm theory. It is worth noting that the instrument for 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 show 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 a 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 7 presents the effect of peers' idiosyncratic shock on consumption patterns. In this case, health shock is the proxy for income shock and is measured as the total days of sickness of the household.[29] The larger the number, the more adverse the shock is. As income may be endogenous to the consumption pattern, using health shocks as a proxy for income shocks allows for capturing a more exogenous variation. Overall, people's consumption patterns in the event of health shocks also support the predictions in the social norm theory. Since the peers' shock variable is not subject to the simultaneity problem, I use the contemporaneous

[29]Health shock is significantly correlated with income. A one percentage increase in sickness decreases income by three percent.

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 effects, I also present the non-instrumented OLS result as a comparison.

According to Prediction 4 in the social norm theory, the negative shock experienced by poor peers should have a positive effect on an individual's 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, and in the IV specification, they are significantly different from zero. Notice that peers' adverse shock has a much stronger positive impact on a household's own temptation consumption than that on a 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. While the number of poor peers may be endogenous, these results in columns 5 and 6 help 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 a 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 between poverty status and health shock in row 4 should be positive. Table 7 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 is more pronounced 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 for 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 on non-temptation consumption relative to the rich, while cutting down less on temptation consumption compared to the rich. Poor households seem to be less resistant to temptation goods. If consuming temptation goods is considered a sign of impatience, the evidence slightly supports income heterogeneity in myopic behavior. Take column 5 as an example, one additional day of sickness can decrease rich households' temptation consumption by 0.182 bahts, while it only decreases temptation by 0.0874 bahts among poor households.

6 Robustness Checks

6.1 Alternative Model: Risk Sharing

Could the observed peer effect result from another mechanism, such as risk sharing (Townsend, 1994)? While risk sharing through social networks can lead to similar peer effects on temptation consumption as the social norm model, it also causes comovement in non-temptation goods. Controlling for total peer consumption, this comovement in temptation consumption would no longer hold, helping to distinguish risk sharing from social norms.

Another way to distinguish the risk-sharing mechanism from the social norm mechanism is by examining the predictions regarding shocks. The risk-sharing model, similar to Fafchamps and Lund (2003), would make the following predictions: (1) Shocks that affect network members will decrease an individual's consumption, including both temptation and non-temptation consumption. (2) Idiosyncratic shocks will have no impact on an individual's consumption, including both temptation and non-temptation consumption, once controlling for network shocks.

In summary, the social norm model and the risk-sharing model yield different results in terms of Predictions 2–4. Table 2 illustrates these differences. First, both models predict a positive correlation between own and peers' temptation consumption. In the second prediction, the risk-sharing model predicts that the coefficient on peers' temptation consumption becomes insignificant when controlling for peers' total consumption. Third, in the risk-sharing model, the coefficient for peer temptation consumption is identical to that of non-temptation consumption. Conversely, the social norm model predicts a larger coefficient for peer temptation consumption compared to non-temptation consumption. Fourth, the social norm theory predicts a significant distinction between more observable and less observable consumption, with stronger peer effects on external alcohol consumption compared to home consumption. The risk-sharing model does not differentiate between these consumption behaviors. Regarding income shocks in the fourth prediction, the risk-sharing model predicts that peers' shock will have negative effects on an individual's temptation and non-temptation consumption, while the social norm model predicts that peers' negative income shock will increase an individual's temptation consumption. Additionally, the social norm model predicts positive effects on total consumption from idiosyncratic shocks, whereas the risk-sharing model suggests no impact when accounting for peer aggregate shocks. Consider these different predictions, my findings support the social norm model as a more plausible explanation than risk-sharing theory.

The previous section contrasts the predictions between the risk-sharing and the social norm model. This section presents several robustness checks. My results support the social norm explanation. However, to ensure that I have processed the data in a consistent manner with previous literature using the same information, I employ the village as the social network definition to test the risk-sharing theory. Similar to Townsend (1994), I use aggregate yearly data to analyze the relationship between household's idiosyncratic income and household's consumption. If risk sharing is in place and efficient, the coefficient on idiosyncratic income should be small and statistically insignificant.

Table B-1 shows the relationship between own income and consumption. The results in columns 1 and 2 indicate the presence of risk sharing at the village level. The coefficient in column 1, although statistically significant, is small. The coefficient in column 2 using the first difference specification is small and insignificant. Idiosyncratic income is not correlated with consumption. However, the 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 interactions. Social norms strongly affect villagers' temptation consumption when observing the behaviors of individuals' peer groups.

6.2 Other Robustness Checks

i) Alternative Timeframe

I further conduct a robustness check using variables from alternative timeframes. This alternative analysis provides insight into the underlying mechanism, as the lagged instrument might necessitate a habit formation assumption alongside peer effects. Concerns may arise regarding the asymmetry in timing, given that I employ lagged consumption to instrument peers' current-period consumption in the first stage,[30] while using both peers' and own consumption variables at the current period. To test whether the results remain robust with a symmetric timeframe, 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 analogous yet attenuated results from this symmetric specification, as there might be a delay in response to peers' temptation consumption, assuming some level of habit formation in consumers' utility function.

Table B-2 shows that, with alternative timeframes, similar peer effects on temptation consumption are observed. However, the results are comparatively weaker compared to the previous finding using instruments at $t-1$, as shown in table 5. In column 3, for example,

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

the coefficient is borderline significant. Likewise, Table B-3 presents rconsistent and robust results for alcohol consumption using a similar timeframe as previously described. Although the effect size is not as strong as in the main regression, this outcome remains plausible in the IV context. It is worth noting that higher-order lag variables might not always serve as effective instruments in practice due to potential weak instrument/identification issues, as noted by Gibbons and Overman (2012).

ii) Sampled Network

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. To address the concern of mis-measured social networks, I conducted robustness check by sampling 50 percent of the observations and re-running the analysis. While it is not possible to recover all the non-sampled network information, this test allows me to assess the strength and stability of the result in the presence of some missing network information. The results, presented in Table B-4 to Table B-6, remain unchanged. The robustness of the results using 50 percent of the sample reduces concerns related to using sampled social networks.

iii) Excluding Alcohol Consumption

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 $tempExAlcohol_{ivt} = \delta_0 + \delta_{tempO} tempExAlcohol_{G_ivt} + \delta_3 X_{ivt} + f_{vt} + \xi_{ivt}$, 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 B-7 presents the results of peer effects on temptation consumption excluding alcohol consumption. The goal of this exercise is to confirm that the peer effects in the main results are driven by social norms rather than being solely driven by the enjoyment of consuming

alcohol together. Column 1 indicates that peers' temptation consumption excluding alcohol consumption has an impact on an individual's consumption excluding alcohol consumption (at 10% significance level). The coefficient on peers' temptation consumption (excluding alcohol) is around 1.6. The positive sign remains in column 2 even after controlling for peers' total consumption, although it is only close to the 10% significance level. Assuming that people do not gamble or buy lotteries together, the significance of the results using temptation consumption on gambling/lottery buying supports the social norm explanation. Based on anecdotal evidence, individuals in these Thai villages typically gamble on their own. Various types of informal gambling exist, such as buying lotteries, betting on stock prices, and participating in fish/chicken fights. Individuals usually place bets at local stores. However, since the results are not as strong as those for alcohol consumption, one should exercise caution when interpreting these results. Nevertheless, the positive sign and magnitude in this analysis still provide some confidence in my social norm hypothesis, even though I cannot entirely rule out other mechanisms.

iv) Alternative Saving Variable

I further investigate the influence of peers' temptation spending on individuals' saving behaviors. Temptation spending captures people's myopic consumption allocation. According to Banerjee and Mullainathan (2010), the concave shape of temptation can impact an individual's saving. Given the data constraints,[31] I use the presence of a saving account for any household member as a proxy for saving behaviors. Table B-8 reveals that peers' temptation spending negatively affects an individual's saving behavior (i.e., they are less likely to have saving accounts based on my definition.). The confidence interval obtained from the CLR test lies entirely in the negative range. Although the IV coefficient is not significant, the CLR test provides a robust result in the presence of weak instruments. However, the magnitude is not as strong as one would have expected, potentially due to limitations in access to the financial system in the local villages. As such, one should interpret this result with caution.

7 Conclusion

Self-control issues often lead individuals to consume multiple types of temptation goods, and this consumption behavior is primarily influenced by peers. Consequently, the "self-control"

[31] Some households have negative income, making it unclear whether simply using income minus consumption would yield meaningful results.

problem can be more accurately described as a "group-control" problem. To examine peer effects on temptation consumption, I present a social norm model as the theoretical foundation. According to this model, individuals have a natural tendency to imitate the temptation consumption pattern 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, includes important information regarding social relationships, diverse income sources, and various types of consumption. The empirical results show that peer effects on temptation consumption are mainly driven by social norms: individuals' temptation consumption varies in accordance with the consumption patterns of their peers because they tend to conform with the majority within their social networks. The covariation of group members' consumption is significantly more prevalent for temptation goods than for non-temptation goods. In addition, the results differ depending on the observability of the goods—public alcohol consumption exhibits stronger peer pressure than alcohol consumption at home. In conclusion, the 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 lead individuals to behave more myopically by consuming more temptation goods, saving less money than desired, and missing out profitable investment opportunities. These outcomes can be particularly detrimental 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. The literature has discussed the possibility of regressive sin taxes as temptation goods are generally over-consumed disproportionately among low-income households (Allcott et al., 2018; Lockwood and Taubinsky, 2017). If there exhibit peer effects among such goods, especially among the poor, the government should consider imposing 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 initiate an

open discussion for further research to better understand the optimal implementation of regressive sin taxes, considering the potential over-consumption through network effects.

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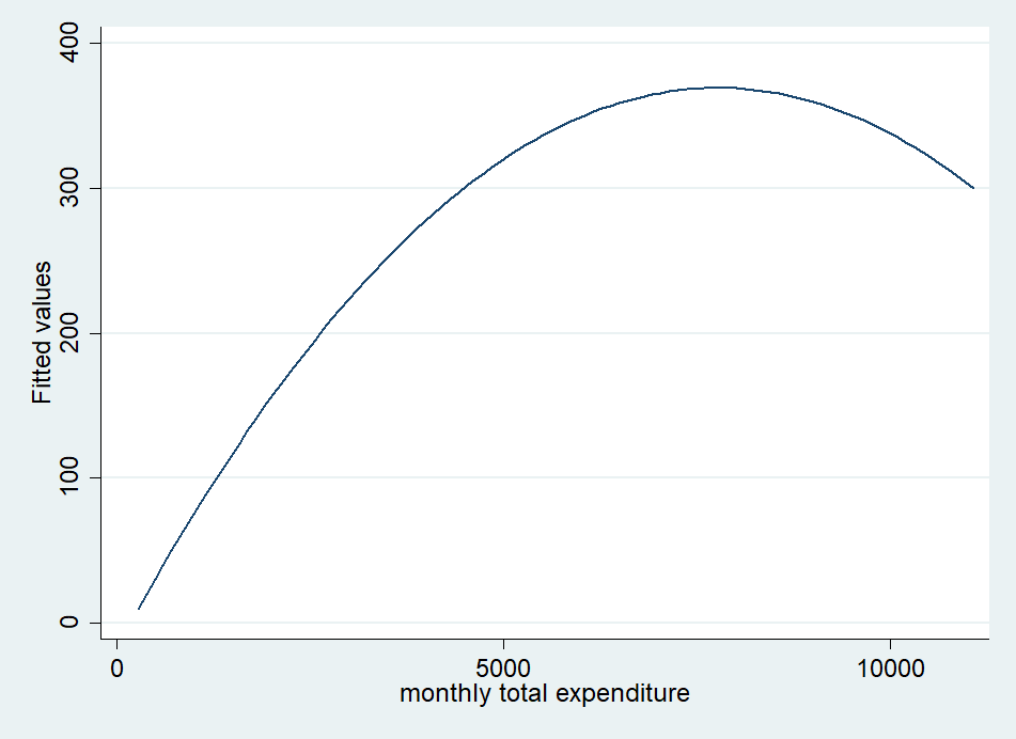
Table 1: Concavity of Temptation Consumption



Note: X-axis represents the "Total Monthly Expenditure" of households per capita, indicating the total amount of money a household spends within a month, with all consumption figures given in Thai Baht (Note: 1 US dollar was equivalent to 40 Thai Baht in 2000). The Y-axis represents the "Households' Total Temptation Consumption", which is defined as the total expenditure that is spent on items such as alcohol beverages, tobacco, lottery, and gambling.

Table 2: 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 3: Summary Statistics

Variable	Definition	Mean	SD	N
Temptation Consumption	Monthly household consumption expenditure on alcohol, tobacco, and gambling	94	212	26,928
Non-temptation Consumption	Monthly household consumption expenditure on all items except for temptation consumption	1,393	3,482	26,928
Total Consumption	Monthly household consumption expenditure on all items	1,487	3,529	26,928
Alcohol Consumption at Home	Monthly household expenditure on alcohol consumed at home	31	158	26,928
Alcohol Consumption Outside	Monthly household expenditure on alcohol consumed outside of the home	12	51	26,928
Sickness	Monthly self-reported sick days of all household members	6.36	15.52	26,928
Temptation Spending Among Total Consumption	Proportion of monthly household expenditure on temptation consumption out of total monthly household expenditure	0.068	0.081	26,928
Household Per-capita Monthly Income	Total monthly household income divided by the number of people in the household	2,872	11,765	26,928
Household Size	Total number of people living in the household	4.37	1.94	26,928

Note: All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000). Temptation consumption is defined as household's expenditure on alcohol beverages, tobacco, lottery, and gambling.

Table 4: Correlation of Social Network

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

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

Table 5: 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
R-squared	0.017	0.010			
Adjusted R-square	0.014	0.007			
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. All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000). Peers are defined as individuals who engage in financial transactions, exchange gifts, or participate in labor-sharing relationships. 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 (2003). Similar to Anderson-Rubin (AR) test, CLR test gives robust confidence set under weak instruments. Yet, CLR test outperforms AR test in power simulations (Andrews et al 2006).

Table 6: 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

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. All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000). Peers are defined as individuals who engage in financial transactions, exchange gifts, or participate in labor-sharing relationships. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i.

Table 7: 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

All dependent variables are the level of household's per capita monthly consumption. All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000). Peers are defined as individuals who engage in financial transactions, exchange gifts, or participate in labor-sharing relationships. Peer's health shock is instrumented using contemporaneous shock information of individual i's friends of friends who are not directly linked with i.

8 Appendix B

Table B-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. All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000).

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

Table B-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 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. All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000). Peers are defined as individuals who engage in financial transactions, exchange gifts, or participate in labor-sharing relationships. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i. 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 B-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

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. All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000). Peers are defined as individuals who engage in financial transactions, exchange gifts, or participate in labor-sharing relationships. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i. 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 B-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 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. All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000). Peers are defined as individuals who engage in financial transactions, exchange gifts, or participate in labor-sharing relationships. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i. This specification uses a sample randomly drawn from 50% of the original dataset.

Table B-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

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. All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000). Peers are defined as individuals who engage in financial transactions, exchange gifts, or participate in labor-sharing relationships. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i. This specification uses a sample randomly drawn from 50% of the original dataset.

Table B-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

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. All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000). Peers are defined as individuals who engage in financial transactions, exchange gifts, or participate in labor-sharing relationships. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i. This specification uses a sample randomly drawn from 50% of the original dataset.

Table B-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 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. All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000). Peers are defined as individuals who engage in financial transactions, exchange gifts, or participate in labor-sharing relationships. Peer's consumption is instrumented using lagged consumption of individual i's friends of friends who are not directly linked with i.

Table B-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. 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. All the consumption figures are per capita monthly spending in Thai Baht (1 US dollar=40 Thai Baht in 2000). Peers are defined as individuals who engage in financial transactions, exchange gifts, or participate in labor-sharing relationships. 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 (2003). Similar to Anderson-Rubin (AR) test, CLR test gives robust confidence set under weak instruments. Yet, CLR test outperforms AR test in power simulations (Andrews et al 2006).

9 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:

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

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

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.