An Empirical Investigation of Risk Sharing among Indonesian Households

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ARTICLE HISTORY
Compiled September 11, 2018

ABSTRACT
This study investigates the barriers to risk-sharing among Indonesian households. We test alternative risk sharing models, namely full risk sharing, borrowing-saving, saving only, hidden income, moral hazard and limited commitment among households. Based on three waves of the Indonesia Family Life Survey (IFLS) dataset, we find that the full risk-sharing hypothesis fails. A nested regression framework suggested by Kinnan (2017) provides evidence in favor of the hidden income hypothesis. However, such a nested framework is unable to discriminate between moral hazard and limited commitment. This motivates us to resort to a non-nested framework. Within this non-nested framework, we test two risk sharing models: (i) the Kocherlakota and Pistaferri (2009) moral hazard model with full commitment and (ii) the Ligon et al. (2002) dynamic limited commitment model. IFLS data reject (i) but there is evidence of (ii). Based on this, we conclude that there are two hidden barriers to risk sharing among the IFLS households, namely hidden income and limited commitment.

KEYWORDS
credit access, risk sharing, limited commitment

1. Introduction

Households in developing countries are vulnerable to income risks which could emanate from various sources such as crop failure, job-loss, illness, accident to name a few. In the presence of full insurance, these idiosyncratic risks can be pooled by the insurance markets and an individual's consumption is freed from dependence on his own income. However, the absence of perfect insurance arrangement is pervasive in many emerging countries as they do not have a well-developed financial system. Due to the absence of proper insurance markets, households in these economies make informal risk sharing arrangements. There is a growing literature documenting this kind of risk sharing arrangement (Collins et al., 2010; De Weerdt and Dercon, 2006; Fafchamps and La Ferrara, 2012; Platteau, 1991; Udry, 1994, among others).

In this paper, we investigate the mode of risk sharing among the Indonesian households. As one of the emerging economies, Indonesia has been struggling in developing

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its financial systems. Majority of the population still have difficulty in accessing financial services. Households, particularly those who are working in the informal sectors and in rural areas, have little or no access to insurance and are often not aware of any basic social security provided by the government. These people are vulnerable not only to idiosyncratic or individual risks, but also to aggregate risks. For example, Thomas and Frankenberg (2007) show that the financial crisis in 1997 has affected households in Indonesia across the board. They also found that there was a significant increase in the incidence of poverty and a decline in living standards as the crisis unfolded. The effects were indicated by lower levels of consumption and income, decrease in households' assets and a reduction in human capital investment.

Our study is inspired by Kinnan (2017) who performs a similar exercise using panel data for Thai households. While Kinnan uses Thai panel household data to test alternative risk sharing models, we use a large panel of Indonesia Family Life Survey (IFLS) dataset to test alternative risk sharing models. Kinnan conducts all the empirical tests based on an econometric specification that nests alternative risk sharing models. We go beyond Kinnan's *nested framework* and test new risk sharing models which cannot be nested. The IFLS micro dataset is quite rich and detailed to enable us to undertake these tests using relatively recent models of risk sharing in the presence of private information and limited commitment.

Using three waves of a panel data of IFLS households, we first undertake a test of a standard full risk sharing among households which requires that each household's consumption should not depend on its own income if the risk sharing is perfect. After adequately controlling for community waves and household fixed effects, we find that the full risk sharing hypothesis is overwhelmingly rejected by the IFLS data. In the next step, we test five extant models of risk sharing using a nested framework suggested by Kinnan (2017). These five models are namely, (i) borrowing-saving (PIH), (ii) liquidity constraint or saving only, (iii) moral hazard, (iv) limited commitment and (v) hidden income. Our IFLS data reject borrowing-saving and saving only models and lend support to the hidden income hypothesis.

Kinnan's nested framework is unable to distinguish between moral hazard and limited commitment scenarios. To get a better understanding of the risk sharing mechanism, we, therefore, resort to non-nested frameworks. We dissociate moral hazard from limited commitment by picking the model of Kocherlakota and Pistaferri (2009) which provides a testable hypothesis when there is private information about efforts and types of agents but the risk sharing contract is subject to full commitment. We call this the *moral hazard only* model. Our test with the IFLS waves rejects this model.

Given that *moral hazard only* model is rejected by the IFLS data, the next test candidate is limited commitment hypothesis. With limited commitment, households stay in an informal risk sharing network which thrives on an arrangement of "quasi credits" designed for mutual insurance as described in several studies such as Fafchamps and La Ferrara (2012) and Udry (1994). In most cases of such informal risk sharing networks, there are no legal record or procedure to enforce repayment. The system is thus vulnerable to reneging. For a sustainable informal risk sharing community network, it is important that the long term benefit of helping each other in the risk sharing network must exceed the short term cost of making a sacrifice. We pick a model of dynamic limited commitment à la Ligon et al. (2002). In such a model, in order to stay in a network with limited commitment, each household follows a simple updating rule for the ratio of its own marginal utility consumption to the marginal utility of consumption of the rest of households in the community. In this environment, the marginal utility ratio *history dependent* if some households in the network are constrained in the sense that they receive minimum surplus from staying in the network. More constrained households put strains on the limited commitment network because these households have to be compensated more by unconstrained households to stay in the network. Thus history dependence of marginal utility ratio suggests that such limited commitment network is likely to be fragile. Since there is no moral hazard element in this model, we call it a *limited commitment only* model. We find some evidence in favor of limited commitment among the IFLS households.

2. Related Literature

Some early papers on risk sharing tests assumed complete market hypothesis to explain consumption insurance across households. Moreover, the risk sharing hypothesis at the household level is calibrated and tested using very rich data sources such as US Panel Study Income Dynamics (Cochrane, 1991) and US Consumer Expenditure Survey (Mace, 1991). However, empirical investigations of full risk sharing using micro data tend to reject the efficient risk sharing hypothesis. Using consumption, labor supply and wage data in the United States, Attanasio and Davis (1996) conclude that consumption risk sharing is incomplete.

The incomplete consumption risk sharing could be due to lack of access to the credit markets. Using cross country data, Beck et al. (2008) develop various indicators of banking services and show the linkages with economic development. Foster (1995) argues that imperfect and segmented credit markets in Bangladesh account for the fluctuations in child growth in rural areas.

Barriers to credit market could induce households to form risk sharing unit within a village or a community. Within a community, the mechanism may take place between families and friends who facilitate risk sharing between economic agents, for instance between young and old, and between families in specific regions. Simply, this can happen because there is mutual assistance among them. This becomes important particularly for low-income and developing economies where access to finance is absent or limited and risk becomes ubiquitous. The insurance mechanism is usually conducted via state-contingent transfers such as in Townsend (1994) and Udry (1994).

However, such informal risk sharing arrangement is fragile due to the immutable limited commitment of group members. The transfers between households in an implicit contract may not occur perfectly if an individual does not comply with the group's terms and conditions. Another possible reason is that usually there is no collateral when risk sharing groups emerge. Ligon et al. (2002) develop a dynamic contract theoretic model to derive the efficient consumption allocations in village economies and test the model using Indian villages. We use their framework to test the risk sharing subject to limited commitment among the IFLS households.

In the Indonesian context, Ravallion and Dearden (1988) study risk sharing in terms of private transfers between Javanese households in Indonesia using 1981 Susenas data. They find a difference between rural and urban households in terms of transfer behaviour. Okten and Osili (2004) utilize IFLS1 and IFLS2 datasets to investigate how consumption smoothing may occur from accessing the credit market. They find that social and community networks are important in gaining access to credit markets. Witoelar (2013) studies how risk sharing emerges within families using IFLS dataset. However, there is hardly any study that investigates the barriers to insurance and alternative forms of risk sharing specifically among Indonesian households.

3. A Survey of Key Models of Risk Sharing

In this section, we provide a brief survey of a few core models of risk sharing which are taken to the data. The main thrust of this brief survey is to understand the structure of the reduced form consumption-income relationships of households. This survey highlights that different risk sharing arrangements imply different testable reduced form consumption processes.

3.1. *Full Risk Sharing*

The perfect risk sharing model is based on the assumption of complete markets as in Arrow and Debreu (1954) and Arrow (1964), widely known as the Arrow-Debreu model. Under full insurance, each household's consumption does not move in unison with its own income because households can use the asset markets to pool individual income risks. To test this, we can use Townsend's (1994) standard test of full risk sharing using all waves of data. The key risk sharing equation is given by:

$$\ln c_{i,t} = \alpha \ln y_{i,t} + \theta_i + \gamma_j + \varkappa_t + \gamma_j \varkappa_t + \varepsilon_{it} \tag{1}$$

where $c_{i,t}$ denotes household i's consumption at date t, $y_{i,t}$ denotes household i's income at date t , θ_i represents the household fixed effect, γ_j denotes village or community fixed effect, $\varkappa_t$ denotes wave effect, and ε_{it} denotes irregular noise. We also allow for an interaction between village and wave effects to allow for each village to have its own aggregate shocks. The key null hypothesis is $\alpha = 0$. If the term α is significant, it implies that household i's income tracks its consumption. This means rejection of full risk sharing hypothesis.

3.2. *Limited Risk Sharing*

If full risk sharing breaks down, several possibilities of limited risk sharing lend themselves. Households may operate in an incomplete market environment with an access to borrowing and lending at a risk-free rate. We call these models as *borrowing-saving* or *permanent income hypothesis* (PIH) models because these models are mostly designed to smooth consumption over time in the spirit of traditional permanent income hypothesis.[1] Hall (1978) shows that in such an environment the Euler equation characterizing the household's optimal consumption path means that marginal utility follows a random walk.

In other words,

$$\beta E_{t-1} u'(c_{it}) = u'(c_{it-1}) \tag{2}$$

where β denotes the subjective discount factor, and $u'(c_{it})$ is the marginal utility of consumption of the i-th household at date t, E_{t-1} is the expectation at date $t-1$. Ligon (1998) interprets Hall's model of permanent income as a scenario of missing insurance markets where agents basically share a common intertemporal marginal rate of substitution which equals common marginal rate of transformation in production. With isoelastic utility function, this means that the expected consumption growth

[1] Of course the notion of consumption smoothing can be broadened to include full risk sharing models where the consumption smoothing happens across states.

rate is equal for all households at a given point in time. This leaves the room open for a growing cross sectional consumption inequality as pointed by Deaton and Paxson (1994) and others. The permanent income model, therefore, depicts an extremely limited form of risk sharing where households have little flexibility of risk sharing choice except sharing a common intertemporal marginal rate of substitution in consumption.

One can think of other versions of permanent income model where households may be limited by able to save but not able to borrow (liquidity constrained). This means that the standard Euler equation (2) is not applicable because of liquidity constraints. Following Deaton (1991), this leads to a *saving-only* model where the lagged income may contain information that cannot be captured by consumption in the same period. The current consumption could be then higher than the last period's consumption when the household experiences a low last period income. The underlying rationale is that if income is a mean reverting process, a low income shock last period may indicate that a liquidity constrained household who cut back last period consumption would increase today's consumption to smooth consumption over time.

Modern models of risk sharing bring informational frictions as an additional barrier to risk sharing. In a moral hazard model, work effort in the production process is private information to the household. Introducing incentive constraints on the household to elicit effort invalidates full insurance and gives rise to an inverse Euler equation first derived by Rogerson (1985) as follows:

$$\delta E_{t-1} u'(c_{it})^{-1} = u'(c_{it-1})^{-1} \tag{3}$$

The appendix outlines the basic principles behind such inverse Euler equation. Kinnan (2017) uses the methodology of Fernandes and Phelan (2000) and show that such a lagged inverse Euler equation representation is robust when the distribution of income depends on past and the current effort. Besides the shadow price of the resources of the community, the household's inverse marginal utility is independent of all information at date $t-1$. Thus adding household's income on the right hand side of (3) will not provide any additional explanatory power.

When effort is contractible but the community does not observe household's income, it gives rise to another form of barrier to insurance known as *hidden income*. Thomas and Worrall (1990) derive optimal contracting arrangement under which the household finds it incentive compatible not to hide its income. Using this lead, Kinnan (2017) shows that under hidden income, the inverse Euler equation formulation (3) is modified by inclusion of the lagged income (y_{it-1}) with a non-negative coefficient as an additional explanatory variable.

Another friction could emerge if the household could potentially walk away from an insurance network at any time by going to autarky. This form of barrier to risk sharing is known as *limited commitment*. To prevent such defection, a planner has to impose a participation constraint on the household. Kinnan (2017) shows that such a constraint again gives rise to an inverse Euler equation structurally similar to (3). This gives rise to a difficulty in disentangling a limited commitment model from a standard moral hazard inverse Euler equation.

3.2.1. A Nested Formulation of Limited Risk Sharing Models

Kinnan (2017) uses the inverse Euler equation (3) to nest five models of limited risk sharing namely, (i) borrowing-saving (PIH), (ii) liquidity constraint or saving only, (iii) limited commitment, (iv) moral hazard, and (v) hidden income. Rewrite (3) the inverse of teh current marginal utility as a function last period's inverse marginal utility and the shadow price of village's resource (η_t) and adding a lagged income term (y_{it-1}) lagged:

$$E_{t-1}\frac{1}{u'(c_{it})} = f\left(\frac{1}{u'(c_{it-1})}, \eta_t, y_{it-1}\right) \tag{4}$$

If the inverse Euler equation holds, then the past income term should be insignificant. With a *log utility* function (3) can be given a linear specification

$$c_{it} = \alpha c_{it-1} + \beta c_{it-1}\eta_t + \theta\eta_t + \gamma y_{it-1} \tag{5}$$

A distinguishing character of the inverse Euler equation is that the shadow price (η_t) associated with the village's sequential resource constraint appears nonlinearly with the inverse of the lagged marginal utility. In a linear specification of the LIMU specification with log utlity, this nonlinearity is picked up by the interaction term, This interaction term makes the inverse Euler equation look different from a standard Euler equation. Thus while looking for the presence of such LIMU, one has to check whether the interaction term is significant.

We follow Kinnan (2017) to proxy η_t by the leave-out mean of average consumption $\sum_{j\neq i}\frac{c_j}{N_v-1}$ with N_v being the size of the village v. All three models of limited risk sharing, namely (3), (4) and (5) suggest the presence of the multiplicative term $c_{it-1}\eta_t$. If $\beta = \gamma = 0$, it reduces to PIH models (i). If $\beta = 0$ but $\gamma < 0$, then the data lend support for saving only model. If $\beta \neq 0$, $\theta \neq 0$, but $\gamma > 0$ then data support to hidden income hypothesis (v). On the other hand, if β and θ are nonzero but $\gamma = 0$, one cannot distinguish between moral hazard and limited commitment models.

3.3. *Non-nested models of limited risk sharing*

Kinnan (2017) LIMU test is unable to distinguish between moral hazard and limited commitment. Thus the results of the nested regression are difficult to interpret. If the LIMU term is present in the regression, it is not clear whether we have an environment of moral hazard or limited commitment. The non-nested tests that we introduce now are fundamentally different from Kinnan's formulation. KP (2009) model involves households agreeing to long term contract to elicit effort and type. Adherence to such a long term contract means full commitment. On the other hand, in Kinnan (2017) the LIMU based test does not have such full commitment. As a result, in Kinnan's setting, we cannot ascertain from the the presence or absence of LIMU term whether IFLS households lack commitment to stay in a network or whether the issue is a simple private information problem of moral hazard or adverse selection. Lack of commitment means that even if agents are a given a long term incentive compatible contract not to lie about effort and type, they may not adhere to this contract because the short term gain from reneging may outweigh the long term loss of going to an autarky. Thus moral hazard and limited commitment need to be conceptually separated. This explains why we separately test two non-nested models.

3.3.1. Kocherlakota and Pistaferri (2009) moral hazard model

KP introduce *ex ante* information friction which means that before entering a risk sharing contract, an agent does not know the efforts and skills of other agents in the risk sharing group because these effort and skill types are private information. Kocherlakota and Pistaferri (2009) show that in such an environment with private information, one can construct a constrained social planning problem where a risk neutral social planner internalizes the agency costs of these private information. KP derive the efficient contracting arrangement of this scenario by setting up a constrained social planning problem where the social planner offers a contract of consumption and work effort to the participating households in a community which maximizes their expected utility subject to two constraints, namely (i) a participation constraint ensuring not to walk away to an autarky, and (ii) a truth telling constraint which means that the household has no incentive to shirk or misrepresent its type. KP derive the same LIMU by solving a cost minimization problem as in Rogerson (1985) *a la* Mirrlees (1999). This cost minimization problem is outlined in the appendix.

KP environment is relevant in the present context because households may join a community and agree to exert effort by revealing their skill types to produce output for the community. An example is the case of households forming an informal group to cultivate crop for the community. Household's income is not private information but its effort and productivity are. In such a scenario, the household has an incentive to shirk (moral hazard) or misrepresent its type (adverse selection). The first order condition again gives rise to an inverse Euler equation as in (3). Invoking the law of large numbers, Kocherlakota and Pistaferri derive the following stochastic discount factor ($sdf_{t-1,t}$) based on cross sectional raw moments of consumption of the households in the community between dates $t-1$ and t which they call Private Information Pareto Optimal (PIPO) sdf:

$$sdf_{t-1,t} = \frac{C^{\varrho}_{t-1}}{C^{\varrho}_{t}} \tag{6}$$

where C^{γ}_{t-1} is the γ^{th} cross sectional raw moment in the community at date $t-1$ and ϱ is the relative risk aversion parameter. The appendix shows an outline of the derivation of the raw moments condition (6). Due to the application of law of large numbers, this *sdf* is robust to the stochastic process generating household's hidden skills and thus it does not depend on household's longitudinal history of characteristics. In addition, it is robust to possible mismeasurement of consumption. This makes the KP formulation quite a useful test strategy using limited waves of data.

To reiterate, the moral hazard environment of KP model is theoretically different from Kinnan's formulation. In KP's moral hazard model, a social planner solves a constrained allocation problem where it is incentive compatible for the households to reveal its type and effort and participate in such a contract market that opens only once at the start of time. This contract is, therefore, a *full commitment contract* which means that the household after signing such a contract cannot renege or re-contract. Thus we call KP a model of *moral hazard only.*

The PIPO sdf can be applied to a wide class of incomplete market environments.[2] Applying this to a simple credit market environment as in the preceding consumption smoothing model where households have access to borrowing and lending at a gross risk free rate R, the standard Euler equation can be written as:

$$E_{t-1}\frac{RC^{\varrho}_{t-1}}{C^{\varrho}_{t}} = 1 \tag{7}$$

[2]Basu and Wada (2006) apply this PIPO discount factor to test international risk sharing.

which E_{t-1} is the expectation operator at date $t-1$. Taking the log-transform and assuming homoskedastic errors, we can rewrite (7) as a regression equation as log-linear random walk process for the γ^{th} cross-sectional raw moment of consumption,

$$\ln C_t^{\varrho} = a + \ln C_{t-1}^{\varrho} + \varepsilon_t \tag{8}$$

where a denotes a constant and ε_t denotes the residual error. Motivated by this random walk specification of the cross sectional raw moments, we propose the following regression to test Kocherlakota and Pistaferri's risk sharing model of private information (2009) for each community:

$$\ln\left(\frac{\sum_{i=1}^{N_k} c_{ik,t}^{\varrho}}{N_k}\right) = \alpha_0 + \alpha_1 \ln\left(\frac{\sum_{i=1}^{N_k} c_{ik,t-1}^{\varrho}}{N_k}\right) + \alpha_2 \ln y_{k,t-1} + \theta_k + \varepsilon_{k,t} \tag{9}$$

where $c_{ik,t}$ is household i's consumption in community k at date t, $y_{k,t}$ denotes average income at community k at date t, θ_k denotes the community-fixed effect, and $\varepsilon_{k,t}$ denotes error terms. N_k is different from community to community. If this risk sharing environment is true, α_1 should be close to unity and no other variables such as past income of the community should have any additional explanatory power in determining the left hand side cross sectional raw moment which means that α_2 should equal zero for a plausible range of risk aversion parameter, ϱ.

There are two advantages of this moment based first order condition vis-à-vis the LIMU first order conditions used by Kinnan (2017). First it is immune to the classical measurement error problem as shown by KP (2009). Second, because of the application of law of large numbers, one does not need longitudinal data on household consumption. All we need is a time series of cross section of households who may not necessarily need to be observed in all successive waves.

3.3.2. Dynamic Limited Commitment Model of Ligon et al. (2002)

The contract stipulated by KP is not time consistent due to full commitment assumption. Agents can sign such a contract at date zero but renege on it at a later date due to limited commitment. Thus limited commitment needs to be modelled separately in a non-nested framework. In the Ligon et al. (2002) model of limited commitment, households form an informal risk sharing group with a "quasi credit" arrangement. There are no written records, legal provisions, or collateral to enforce repayment. There is an implicit understanding that there may be delay in repayment or forgiving of the debt in extenuating circumstances. Agents still form such informal risk sharing arrangement because the perceived long term benefits of adhering to such group may outweigh the short term costs. Assuming a finite state Markov process for income, Ligon et al. consider first a bilateral risk sharing arrangement where it is not incentive compatible for any of the households to break away from such a contract and go to autarky. In this model, agents are subject to participation constraints and there is no issue of private information about effort and type. This makes the Ligon et al. (2002) model a *limited commitment only* model without any issue of moral hazard.

The underlying idea of Ligon et al. (2002) is that a planner transfers income across households to ensure that the long term benefit in terms of future consumption insurance outweighs the short term costs. To get the basic intuition, consider a two household scenario, if a transfer is made from household 1 to household 2, the first household's current utility declines. If the transfer is such that this household on the verge of sacrificing all its current income then we call this particular household constrained because he hits the lower bound of feasible consumption. If no household is ever constrained due to the transfer, then the marginal utility ratio is constant over time which means that the marginal utility of each household grows at the same rate. this means that marginal utility ratio is state independent. On the other hand, if the current income state is such that household 1 is constrained, then its marginal utility growth will be different from the unconstrained household. This means that the current marginal utility ratio is history dependent. The appendix outlines the formal derivation of the law of motion of marginal utility ratio.

Ligon et al. (2002) then extends the model to multiple households which is a more realistic scenario. They use a CRRA specification of the utility function and exploit the fact that they are Gorman aggregable to construct an aggregate household representing all in a community except a specific ith household whose risk sharing behaviour is modelled with the rest of the village. Based on this principle, the marginal utility ratio of the ith household to the rest of the household in a village will be history dependent if some households are constrained. Motivated by this argument, we posit the following regression equation:

$$\frac{c_{it}}{\bar{c}_{-i,t}} = \alpha_0 + \alpha_1 \frac{c_{it-1}}{\bar{c}_{-i,t-1}} + \alpha_2(\text{household and village characteristics}) \ + \xi_{it} \tag{10}$$

where $\bar{c}_{-i,t}$ denotes the average consumption of all households in the same village except the i^{th} household and ξ_{it} denotes random disturbance term. These household/village characteristics could be of various kinds, namely existence of formal risk sharing arrangement, proximity to formal financial institutions, relative preponderance of urban to rural households. After controlling for all these effects, if α_1 is found to be statistically significant, it means history dependence of the consumption share of a participating household in the community. This can be viewed as an evidence of dynamic limited commitment in the risk sharing arrangement where some households are constrained to keep the limited commitment network viable. On the other hand, a lack of history dependence ($\alpha_1 = 0$) does not necessarily mean an absence of limited commitment risk sharing. It only means that none of the participants in the risk sharing network is constrained in the sense that he/she is held down to the minimum surplus to keep this risk sharing arrangement viable. In the absence of such corner solutions, the consumption ratio remains time invariant which replicates a first best risk sharing scenario within a limited commitment framework where all participants are happy with the proposed transfers made by the planner. If α_1 is not zero, it points out to a possibility of some constrained households within a limited commitment network for whom autarky seems to be a more attractive option. This can be interpreted as some form of fragility in the limited commitment network. Thus the first best allocations and autarkic allocations are both nested in this model. Ligon et al. (2002) point out that in a multi household economy, there may be several constrained households with alternative consumption sharing rules. Households who are not constrained must finance the consumption of the constrained households. Since it is not known *a priori* who are constrained who are not, one cannot predict an unambiguous sign of α_1 in this environment. All that we can say that if α_1 is significantly different from zero, some households are constrained within the limited commitment network.[3]

[3]Ligon et al. (2002) undertake a detailed structural estimation of their model. In this paper, we focus on the reduced form consumption share equation with a primary goal to ascertain whether a limited commitment

Table 1 summarizes all the risk sharing arrangements reviewed in this section.

[Table 1 about here.]

4. Data

All our data are gathered from the Indonesia Family Life Survey (IFLS). These longitudinal surveys consist of two levels: community and household surveys where the latter can be decomposed into individual and family levels. There are four waves available: IFLS1 in 1993 (Frankenberg and Karoly, 1995), IFLS2 in 1997 (Frankenberg and Thomas, 2000), IFLS3 in 2000 (Strauss et al., 2004), and IFLS4 in 2007 (Strauss et al., 2009). In IFLS, around 90% of sample households are retained from the first wave until the latest which is considered to be the advantage of using this dataset to make an economic analysis of risk sharing and related testable implications. For this study, we only use IFLS data up until Wave 3.[4]

For the empirical analysis, we make sure that the data fulfill some basic conditions: (i) all necessary information regarding household variables are available, meaning that only households that exist for all waves are considered, (ii) relevant variables, particularly consumption and income, do not take extreme values[5]; and (iii) households stay within their villages for the whole period. In IFLS1, the number of households is 7,224 while in IFLS3, there are 10,435 households. However, due to incomplete information, we are only able to use 3,194 households across the waves.[6]

For testing the Kinnan (2017) nested regression model, Kocherlakota and Pistaferri (2009) model and Ligon et al. (2002) model, we cannot use the whole sample due to the restriction imposed by the balanced nature of the panel. Many households cannot be observed across two successive waves mostly due to family migration and incomplete household characteristics such as employment and socio-economic status. In most cases, we work with around 3,116 households who live in 310 villages or communities.

The consumption is measured by per capita expenditure (PCE) and the income is also measured by per capita income (PCI). This means that the consumption and income for each household is divided by the number of people living in that household. For the last two waves, around one third of IFLS households have five or more persons living within a household. Households with 2, 3 and 4 persons are relatively similar for waves 2 and 3 surveys. The descriptive statistics for relevant analysis are given in Table 2.

[Table 2 about here.]

[Figure 1 about here.]

[Figure 2 about here.]

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environment exists.

[4] We cannot utilize IFLS4 data due to inadequate information about the consumption data making it difficult to compare across waves.

[5] Extreme values are defined as five percentiles from the top and bottom of the distribution.

[6] The similar number of households is observed in other studies that employ IFLS data, for example Witoelar (2013).

To examine private information model with moral hazard only, we use information at community level by summing up all household consumption and income within a community which is the same as village in the IFLS data. We then compute raw moments for all communities in IFLS using (9) in order to assess risk sharing model with private information.

To test dynamic limited commitment models as formulated in (10) we use community (or village) as a risk sharing unit. Since in the dynamic limited commitment model our aim is to test for the memory of the contractual arrangement, it is important that we have a balanced panel with the same households observed in two successive waves. This restricts us to waves 2 and 3 with about 3008 households. We use village data that exist from IFLS1 to IFLS3. This leaves us with 310 villages or communities for this test. Based on IFLS1, the average number of households within a community is 16.5 households. Each household's consumption in a community is divided by the average consumption of all households in the same community based on the regression Equation (10).

To assess risk sharing within communities, the IFLS provides information about community participation known as Rotating Saving and Credit Associations (ROSCA for short) for each respondent along with individual social and economic characteristics. ROSCAs (or *arisan*) have long been known in Indonesia as a part of the social and economic tradition. Indonesian households use various forms of ROSCA to share their risk. With diverse demographic characteristics, ROSCAs are generally formed by group of people who usually congregate weekly and pass part of the pooled assets in certain ways using either a random pot or a systematic rotation scheme. Since ROSCAs use a simpler approach to conducting financial contract than formal financial institutions, a lot of people, especially those who are credit constrained, prefer to use it as a risk sharing vehicle. In our dynamic limited commitment regression we add ROSCA as an intercept as well as slope dummy to check whether the presence of ROSCA in a village makes any difference to household's risk sharing arrangement.

4.1. *Choice of instruments*

All the reduced form consumption income regressions for various risk sharing scenarios suffer from two potential problems. The endogeneity of income change and the measurement errors could bias the OLS estimates. One could use 2SLS instrumental variables (IV) to remedy this bias. The choice of IVs is always a challenge. The set of IVs should be guided by economic intuition and it should pass a battery tests for underidentification and overidenfication of the model.[7] In addition, reasonable care should be taken to ensure that IVs are not weak.[8]

[7]These tests involve several diagnostics. First, IVs must pass the necessary order order condition which requires that the number of instruments is at least as large as the number of endogenous variables. Second, a rank condition must be checked which requires that the matrix that transforms the IVs to the endogenous variables has a full column rank. The failure of this rank condition means that regression equation is under identified. The Kleibergen-Papp rk LM statistic tests the null hypothesis that the model is underidentified Hansen's J statistic tests whether the overidentifying restriction that the covariance between the IVs and the error term is met. Finally, the researcher has to evaluate whether the choices of IVs are not too weak. The weak-instrument problem arises when the correlations between the endogenous regressors and the excluded IVs are nonzero but small. A good survey of these tests are available in Baum et al. (2007).

[8]Bound et al. (1995) and Staiger and Stock (1997) have shown that weak IV problems can easily arise even when the correlations between the endogenous variables and the IVs is strong. Weak IVs can create bias for IV regressions. The issue is how serious is this bias compared to the bias in OLS regression. Stock and Yogo (2005) propose Wald F test which forms the foundation of Cragg and Donald Wald F test and Kleinbergen-Papp rk Wald F stat. The problem with these tests is that there is no clearly defined critical value for rejecting the

Our choice of IVs is guided by economic intuition. We use IVs when we feel that there is a need for it. The classical measurement error could cause attenuation bias which means downward bias in the estimate of interest. Such an attenuation bias is not an issue for testing full risk sharing hypothesis because in all specifications, we reject the full risk sharing hypothesis. Thus no IVs are used for the full risk sharing regression. For nested regression also, Kinnan (2017) suggests that IVs may lead misleading inference and therefore, we stick to OLS regression. For non-nested regressions we use IVs only to test the KP model of moral hazard because of the presence of a lagged income term on the right hand side giving rise to potential bias in the OLS estimate.

Two sets of instrumental variables (IVs) for household and community level tests are used. For household level, we use health measure which is proxied by the activities for daily living (called ADL hereafter). ADL is a measure that indicates the physical ability of an individual to perform daily living activities. The reliability and validity of ADLs have been tested extensively, mainly in the United States and Southeast Asia. The ADL is transformed into an index as follows:

$$\frac{ADL\ Score - Min.\ Score}{Max.\ Score - Min.\ Score}.$$

The ADL index takes on values from 0 to 1, where zero is when the individual cannot perform any ADLs at all and one is when the individual can easily perform all of the ADLs.[9]ADL is deemed to be a good instrument because it is likely to be strongly correlated with income because individuals with greater physical ability are likely to generate more income. activities for daily living (called ADL hereafter). ADL is a measure that indicates the physical ability of an individual to perform daily living activities. The reliability and validity of ADLs have been tested extensively, mainly in the United States and Southeast Asia.[10] The justification for using ADL as a household level IV is that households with greater physical ability are likely to generate more income because of higher productivity.

At a village or community level, we use rainfall as an IV following Kinnan (2017) and several other studies. Since most of the regions in Indonesia are dominated by agricultural occupation, rainfall is an effective instrumental variable (Fichera and Savage, 2015, for example). The daily rainfall data are obtained from the Indonesian Agency for Meteorological, Climatological and Geophysics (BMKG). We use the previous year's average precipitation for each IFLS wave respectively, then match these data using community data using altitude and longitude to nearest BMKG weather station. The data from 25 BMKG stations are matched with 310 IFLS communities. The matching process is done by calculating a community location to the nearest station.

null. Stock and Yogo (2005) present a range of critical values for various tolerances of the relative bias of IV and OLS as well as the size of the test. A rule of thumb of F equal to 10 is proposed by Stock and Yogo (2005). However, these tests are based on the assumption of iid errors and have to be used with caution. Thus to the best of our knowledge no conclusive critical value for Wald F test is available in the literature. A good practitioner's survey of this literature is available in Baum et al. (2007).

[9]In IFLS, the ADLs are divided into several components. These are namely, ability to carry a heavy load for 20 meters, ability to walk for 5 kilometres, ability to walk for 10 kilometres, ability to bow, squat and kneel, ability to sweep the house floor, ability to draw a pail of water from a well, ability to stand up from sitting on the floor without help, ability to stand up from sitting position in a chair without help, ability to bathe without help, and ability to dress without help. The first four activities are classified as intermediate ADLs, while the last five activities are classified as the basic ADLs.

[10]Gertler and Gruber (2002) provide more explanation about the reliability and validity of ADLs in this regard.

5. Empirical Results

5.1. *Full Risk Sharing Tests*

Regarding the full risk sharing hypothesis, the key question is whether villagers share risk within and across the village. If they do, their consumption should not be correlated with their income. To set the stage for these tests, we first report visual pilots of consumption and income of all households. Figure 1 reports the community consumption against income for all three waves. Across the three waves, the average correlation between community consumption and income is 65%, with the highest correlation is 87.6% for IFLS3. Figure 2 reports the same plot after purging out the village fixed effects from consumption and income. The correlation between consumption and income after purging out is similar across the waves and the average correlation is 67.5%. In both figures, data show a pronounced positive relation between consumption and income. This lends to a strong possibility of absence of full risk sharing among IFLS households sharing either within or across the communities.

Next, we conduct formal tests given the regression Equation (1). The results are presented in Table 3 for five specifications. Column (1) reports OLS results with random effects only which means $\theta_i = \gamma_j = \delta_t = 0$. Column (2) reports the regression after adjusting for heteroskedasticity including household fixed effects but without any village and wave effects which means $\theta_i \neq 0$, and $\gamma_j = \delta_t = 0$. Column (3) reports results with heteroskedasticity adjustment with all three effects included which means $\theta_i \neq 0$, $\gamma_j \neq 0$, and $\delta_t \neq 0$. Column (4) reports the OLS regression with $\theta_i \neq 0$, $\delta_t \neq 0$ and by computing the clustered standard error to allow correlation between IFLS households' unobservable within each village. Column 5 reports the test results when an interaction between community and wave is taken into account. All these five specifications reject the full risk sharing hypothesis because the estimate of the log of income is significant at the one percent level. F statistics indicate that the all these fixed effects are jointly significant.

[Table 3 about here.]

5.2. *Nested regression*

Given that the full risk sharing hypothesis is overwhelmingly rejected by the IFLS data, we next turn to testing limited risk sharing models. Table 4 reports the results of the nested regression (5) for alternative limited risk sharing models. We follow Kinnan (2017) by undertaking an OLS regression adding the village-wave fixed effect via the term η_t. We do not run a conventional fixed effect regression to avoid Nickell (1981) bias due to limited number of waves.

While testing the nested regression (5), one encounters challenges. Kinnan (2017) points out that the measurement error on the right hand side variables can affect the size of the test and cause the over rejection of the inverse If consumption has classical measurement error, the estimated coefficient β in (5) will be attenuated towards zero and this can bias the test against the hypothesis of moral hazard and limited commitment and favour hidden income. Kinnan points out that this creates misspecification which cannot be solved a standard IV approach. We, therefore, conduct all the tests in nested specifications using standard OLS regression.

[Table 4 about here.]

Tables 4 reports the key results of nested regressions for the whole sample. The saving only model is clearly rejected because $\gamma > 0$ and is significant at the 1% level. Since β, θ are also statistically significant from zero, one cannot reject the hidden income hypothesis although the moral hazard and limited commitment scenarios are both rejected.

5.3. *Non-nested models*

We now turn to the test of two non-nested models, namely KP (2009) model of moral hazard only and the dynamic limited commitment model of Ligon et al. (2002). As pointed out earlier both these models are fundamentally different and they cannot be nested by Kinnan's framework.

5.4. *Moral hazard only regression*

Table 7 reports the KP raw moment regression in Equation (9) involving 310 communities for the risk aversion parameter, ϱ. Since the right hand side variable, village income may have measurement error, we use rainfall and ADL as IVs. Since this regression is at the village level, ADL is averaged across all households within each village and the rainfall rate in each village from the previous year is used as the second instrument.

Tables 5, and 6 present the regression results for two specifications: (i) OLS with village fixed effects, and (ii) Random effects approach. The lagged income coefficient is insignificant in all these specifications. In addition, the lagged raw moment coefficient is few away from unity. These specifications thus point towards rejection of the KP moral hazard only hypothesis for a range of risk aversion coefficients between 1 and 2. There is a consensus in the literature that the proportional risk aversion parameter is close to unity. Gandelman and Hernández-Murillo (2015) estimate the coefficient of relative risk aversion (ϱ) at the country level. For Indonesia, their estimate suggests that ϱ is close to 1.2.

To check the robustness of the results, we further carry out a 2SLS-IV regressions with our two IVs, rainfall and ADL averaged across households in each village. The results in Table 7 again reject the KP specification. Our IV diagnostics based on Hansen's J statistic suggests that the over-identifying restriction that two IVs have zero covariance with the error cannot be rejected. Kleinbergen-Papp rk LM statistics indicate that our IVs are reasonably strong.

[Table 5 about here.]

[Table 6 about here.]

[Table 7 about here.]

5.5. *Limited commitment only regression*

We now turn to the limited commitment only model of Ligon et al. (2002) based on the regression in Equation (10). The primary question that we ask here is whether there is a history dependence in the consumption ratio. Such a history dependence signifies that at least one of the participants in the risk sharing network is constrained in the sense that s/he is held down to the minimum surplus to keep this risk sharing arrangement viable. If they are constrained, it will be reflected by a significant coefficient of the lagged consumption ratio. In addition, we also investigate whether the presence of ROSCA households make any difference to the limited commitment risk sharing arrangement of IFLS households. We investigate this by interacting the coefficient of the lagged consumption ratio with the ROSCA dummy and check whether the interaction term is significant. If the interaction term is found significant, it means that households in a ROSCA network are more constrained than the households outside the network.

Table 8 provides the estimation results for limited commitment for various specifications. The first column shows the result of a OLS random effect regression taking into account the heterogeneity of households within and across all villages. This is done by a heteroskedasticity correction of the standard error. The regressions reported in the remaining tables incorporate various types of fixed effects to control for the household and village characteristics in the limited commitment regression (10). The Wald chisquare statistic in column 1 shows that all the coefficients in the random effect regression are jointly significant. The F statistics in the remaining columns confirm that all fixed effects are jointly significant.

Two key observations come out of this exercise. First, the lagged consumption ratio term is significant in all specifications suggesting that there is evidence of constrained households in a limited commitment environment. Second, in three of these specifications, the ROSCA intercept dummy is found significant and positive which suggests that ROSCA households benefit in terms of consumption share within a limited commitment network. On the other hand, the ROSCA slope interaction dummy is found significant in the random effect specification which indicates that the ROSCA households are still constrained compared to the rest of the households in the village network. The upshot of this exercise is that IFLS households are likely to share risk in a limited commitment environment but the risk sharing arrangement appears fragile due to the preponderance of constrained households. Viewed from this perspective, the ROSCA network is also fragile.

[Table 8 about here.]

6. Conclusion

In this paper, we study the barriers to risk sharing among Indonesian households using three waves of IFLS data. Using the extant theoretical literature on risk sharing hypothesis, we test six key risk sharing models. Our study overwhelmingly rejects full sharing among IFLS households. Using a nested regression framework, we also reject standard borrowing-saving and saving-only models. As in Kinnan (2017), we also find evidence of the hidden income hypothesis. Our IFLS data reject a non-nested *moral hazard only* model à la Kocherlakota and Pistaferri (2009). We also test the implications of the limited commitment environment of Ligon et al. (2002). Our panel regressions suggests that although there is evidence in favour limited commitment, households in such a risk sharing network are more likely to be constrained to keep such informal network viable.

The rejection of full risk sharing model and alternative models of risk sharing involving imperfect credit markets is not surprising given the pervasive failure of formal credit and insurance markets in these economies. This gives rise to the possibility of informal networks among the Indonesian households. Our study suggests that these networks are also fragile because of the immutable human incentive to hide income information as well as not to fully commit to the rules of a village network. The bottom-line of these overarching tests of various models of risk sharing is that there are several barriers to risk sharing among IFLS households. These barriers could originate from household's tendency to hide income and work effort. An organization of informal network of risk sharing with limited commitment also appears quite vulnerable because of the preponderance of constrained households.

A long term solution to remedy all these barriers to risk sharing is to improve household's access to credit market by establishing appropriate financial institutions. Given that such macro policies of financial deepening could take time and resources, piecemeal solutions on a case by case basis could help. The ROSCA network with proper monitoring can be expanded to reach more people in a rural economy. In addition, the government could promote the micro credit agencies to access the villages. More innovative local monitoring and moral suasion of people in a network could straighten commitment among the group members. Banerjee and Duflo (2012) provide several case studies of success stories of this kind of moral suasion in the context of rural India. These steps do not necessarily eliminate the problems of hidden income and limited commitment but could help overcome these barriers to risk sharing.

Appendix

KP Private Information Model:

The cost minimization problem facing the social planner can be described as follows. Take away $\delta\Delta_t(i)$ utility from the ith agent with history h_t and returning her $\Delta_t(i)$ in the following period with certainty where δ is the subjective utility discount factor. Such a reallocation leaves the expected utility of the individual constant and thus the relevant incentive and participation constraints unaltered. However, it alters the planner's budget constraint. The reallocation of utils means reallocation of consumption exploiting the fact that $\delta\Delta_t(i)$ utils is equivalent to the inverse utility $U^{-1}(\delta\Delta_t\ )$ of consumption goods at date t. The risk neutral planner thus choose Δ_t such that it minimizes the following cost function

$$U^{-1}(\delta\Delta_t(i)) + E_t\left(U^{-1}(\Delta_t(i))\right)$$

Using a CRRA utility function and exploiting the inverse function theorem, one obtains the following inverse Euler equation[11]

$$c_t^{\gamma}(i) = E_t\left(c_{t+1}^{\gamma}(i)\right)$$

Kocherlakota and Pistaferri (2009) integrate the above inverse Euler equation across all households which means

$$\int c_t^{\gamma}(i)di = \frac{1}{\delta}\int c_{t+1}^{\gamma}(i)di$$

[11]See Basu et al. (2013) for a detailed derivation in a more general framework.

Note that $\int c_t^{\gamma}(i)$ is the γth cross sectional raw moment of consumption. If the household has access to a riskfree borrowing and lending market, we can replace $R = \delta^{-1}$. This proves Equation (6).

The novelty of KP is that they convert this LIMU into a first order condition involving raw moments of consumption using the law of large numbers.

Ligon et al. (2002) Model

For illustration, we mimic the basic model of Ligon and Thomas (2002) to explain the rationale for the key estimable equation (10). Let there be a village with two households 1 and 2 situated in an endowment economy with $y_1(s)$ and $y_2(s)$ as the endowments for state s. Let endowments follow a Markov process with finite number (S) states with transition probability from state s to state r denoted as π_{sr}. Given the current state, denote $u(c_1(s))$ and $v(c_2(s))$ as the instantaneous utility of these two villagers with consumptions $c_1(s)$ and $c_2(s)$ respectively. The planner designs a contract that transfers τ_s from the first villager to the second villager in such a way that the contract is *sustainable* in the sense that neither of these two households have an incentive to renege on this contract in future for any states. This basically requires that if any of these two villagers loses all his income today (short term loss), the discounted value of utility of this contract (long term benefit) will be at least as good as the continuation value of going to autraky. Denote U_r, V_r as the continuation values of the utlity gain from the autarky for these two respective villagers 1 and 2.

The social planner is designing a state contingent transfer today promising continuation values $\{U_r\}$ to the first villager and subject to which the second villager receives the continuation values $\{V_r(U_r)\}$. These promised values are also chosen by the social planner together with the transfer in such a way that the contract is *sustainable.* The solution to this problem generates a constrained Pareto efficient frontier $V_s(U_s)$ which maximizes villager 2's discounted surplus subject to offering the villager 1 at least U_s given the current state s. The Pareto frontier thus solves the following dynamic programming problem:

$$V_s(U_s) = \max_{\tau_s, \{U_r\}} \left[v(y_2(s) + \tau_s) - v(y_2(s)) + \delta \sum_{r=1}^{S} \pi_{sr} V_r(U_r) \right] \tag{11}$$

s.t.

$$u(y_2(s) + \tau_s) - u(y_2(s)) + \delta \sum_{r=1}^{S} \pi_{sr} U_r \geq U_s \tag{12}$$

$$U_r \geq \underline{U}_r \tag{13}$$

$$V_r(\underline{U}_r) \geq \underline{V}_r \tag{14}$$

$$y_1(s) - \tau_s \geq 0 \tag{15}$$

$$y_2(s) + \tau_s \geq 0 \tag{16}$$

where δ is the common utility discount factor, $\underline{U}_r$ and $\underline{V}_r$ are lowest sustainable discounted at state r for these two respective villagers.

Denote λ, ψ_1, ψ_2, ϕ_r, μ_r as the lagrange multipliers associated with (12), (13), 14), 15), (16) respectively. The first order conditions for this problem are:

$$\tau_s : \quad \frac{v'(c_2(s))}{u'(c_1(s))} = \lambda + \frac{\psi_1 - \psi_2}{u'(c_1(s))} \tag{17}$$

$$U_r : \quad - V_r'(U_r) = \frac{\lambda + \phi_r}{1 + \mu_r} \tag{18}$$

and the envelope condition yields

$$\lambda = -V_s^{'}(U_s) \tag{19}$$

The constrained efficient contract is determined by the evolution of the key Lagrange multiplier λ which determines the ex post rate (after the current state s is known) at which household 1's surplus is traded off for household 2's transfer. Given a history of states (say, h_t), if the non-negativity constraints on consumption (15) and (16) never bind there is a unique interior solution where the marginal utility ratio is equal to λ and is independent of the history of states.

Define $\underline{\lambda}_r = -V_r^{'}(\underline{U}_r)$ and $\overline{\lambda}_r = -V_r^{'}(\overline{U}_r)$. Thus $[\underline{\lambda}_r, \overline{\lambda}_r]$ is the range of sustainable marginal utility ratios. If due to any idiosyncratic income shock, any of the non-negativity constraints (15) and (16) binds, then λ goes outside this range. The planner has to craft the transfers to keep the marginal utility ratio within this range. For illustration, let both villagers have an interior solution until today and then a negative income shock makes the villager 1 makes consumption go to the corner which means his marginal utility of consumption goes to infinity. To prevent this, the planner has to transfer him enough so that the marginal utility ratio $\lambda = \underline{\lambda}_r$. This means that the villager 1 will be *constrained* and held down to the minimum surplus $\underline{U}_r$. This makes his marginal utlity grow at a lower rate than villager 2. From this point onward, the history of states will matter in determining the future marginal utility ratio. Thus if any of the households becomes constrained marginal utility ratio becomes state dependent. With a log utility, this marginal utility ratio is the inverse of c_2/c_1. Thus in this simple village economy with two households, if a household is constrained at date t, c_{2t}/c_{1t} will be a function of c_{2t-1}/c_{1t-1}.

In our empirical formulation, we consider the extension of this model to a multi-agent village economy as suggested by Ligon et al. (2002). We examine the evolution of the consumption ratio of the ith household to the average consumption of the rest of the households in the same village.

Acknowledgments

This paper is an extension of Wibowo's Chapter 6 of his PhD thesis. Authors wish to acknowledge two anonymous referees for extremely useful and constructive comments. Thanks are due to John Moffat, Hugo Kruiniger and Kunal Sen for technical guidance. The usual disclaimer applies.

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Table 1. Summary of Risk Sharing Hypotheses and Related Tests

	Specification	Expected Sign
Full Risk Sharing	Eq (1)	$\alpha = 0$
Nested Models of Risk Sharing, Kinnan (2014)		
PIH	Eq (5)	$\beta = \gamma = 0$
Saving Only	Eq (5)	$\beta = 0$ and $\gamma < 0$
Hidden Income	Eq (5)	$\beta \neq 0$ and $\gamma > 0$
Moral Hazard or Limited Commitment	Eq (5)	$\beta \neq 0$ and $\gamma \geq 0$
Non-nested Models of Risk Sharing		
Moral Hazard Only Kocherlakota and Pistaferri (2009)	Eq (9)	$\alpha_2 = 0$
Limited Commitment Only (Ligon et al., 2002)	Eq (10)	$\alpha_1 \neq 0$

Table 2. Summary Statistics of Key Variables

Variable	Obs.	Mean	Std. Dev.	Min	Max
			IFLS1 − 1993		
log(PCE)	3,194	11.9568	0.7732	9.3117	15.645
log(PCI)	3,194	10.3974	2.0141	0.9641	18.6922
ADLs	3,194	0.9672	0.0851	0	1
Rainfall rate	3,194	5.3455	1.597	2.789	9.2575
			IFLS2 − 1997		
log(PCE)	3,194	12.3716	0.7755	9.9135	17.2958
log(PCI)	3,194	11.5133	1.4148	-1.5757	18.8558
ADLs	3,194	0.9673	0.0851	0	1
Rainfall rate	3,039	5.3502	1.605	2.789	9.2575
			IFLS3 − 2000		
log(PCE)	3,194	12.3821	0.7097	10.2886	15.5103
log(PCI)	3,194	11.5633	1.1696	5.6268	17.2419
ADLs	3,194	0.9599	0.0999	0	1
Rainfall rate	2,936	5.3339	1.6018	2.789	9.2575

Per capita income (PCI) and per capita consumption (PCE) figures are in monthly and in 2000 Indonesia rupiah. The values are transformed into logarithmic values. ADLs denote activities of daily living index. Log of household assets are calculated from total value of assets for each household in 2000 Indonesia rupiah. *Source*: authors' calculation from IFLS dataset.

Table 3. Full Risk Sharing: Individual and Community Level

	Log of per capita expenditure				
	(1)	(2)	(3)	(4)	(5)
Log of per capita income	0.170^{***} (0.00643)	0.116^{***} (0.00635)	0.0545^{***} (0.00668)	0.2^{***} (0.00763)	0.0511^{**} (0.00648)
Households	3,194	3,194	3,194	3,194	2983
Observations	9582	9582	9582	9582	8647
R^2	0.0945	0.095	0.239	0.228	0.371
Wald $\chi^2(1)$	699.54				
p-value	0.000				
F-stat		335.5		688.84	8.7e+12
p-value		0.00		0.000	0.000
Estimation method	RE (robust error)	FE (robust error)	FE (robust error)	OLS (clustered-robust error)	FE (robust error)
Fixed effects	No FEs	HH FE only	All FEs	HH & wave only	community×wave

All variables are in 2000 Indonesian rupiah. RE means random effects, and FE means fixed effects. The number of clusters is 310 villages. Coefficients significant at the 10% level are denoted by *, at the 5% level by **, and at the 1% level by ***. *Source*: authors' calculation from IFLS dataset.

Table 4. Nested regressions

	Log of per capita expenditure
Log of previous per capita consumption	0.452***
	(0.0275)
Log of previous per capita consumption$\times\eta$	-0.0543*
	(0.0213)
Log of previous per capita income	0.0285***
	(0.00559)
η	0.289***
	(0.0282)
Constant	4.255***
	(0.248)
Observations	6232
Households	3116
R-squared	0.3219
Wald $\chi^2(4)$	1735.1
Prob > χ^2	0.0000

Note: All variables are in 2000 Indonesian rupiah. η is in log form. Random effects approach is employed to estimate the model. Robust standard errors in parentheses. Coefficients significant at the 10% level are denoted by *, at the 5% level by **, and at the 1% level by ***. *Source*: authors' calculation from IFLS dataset.

Table 5. Moral hazard only regressions using OLS approach

	Consumption moment					
	(1)	(2)	(3)	(4)	(5)	(6)
γ value	1.00	1.20	1.40	1.60	1.80	2.00
Average log of previous income	0.100^{***}	0.144^{***}	0.188^{***}	0.232^{***}	0.275^{***}	0.317^{***}
	(0.0238)	(0.0303)	(0.0372)	(0.0444)	(0.0517)	(0.0592)
Observations	620	620	620	620	620	620
Community	310	310	310	310	310	310
R^2	0.334	0.290	0.256	0.231	0.211	0.196
Adjusted R^2	0.331	0.288	0.254	0.228	0.209	0.193

This table presents moral hazard tests using raw moment simulations based on Equation (9). Community dummies are added to the empirical specifications. All variables are in 2000 Indonesian rupiah. Standard errors are reported in parentheses. Coefficients significant at the 10% level are denoted by *, at the 5% level by **, and at the 1% level by ***. *Source*: authors' calculation from IFLS dataset and BMKG.

Table 6. Moral hazard only regressions using Random Effects approach

	Consumption moment					
	(1)	(2)	(3)	(4)	(5)	(6)
γ value	1.00	1.20	1.40	1.60	1.80	2.00
Average log of previous income	0.104*** (0.0264)	0.148*** (0.0322)	0.193*** (0.0377)	0.237*** (0.0432)	0.281*** (0.0489)	0.322*** (0.0548)
Observations	620	620	620	620	620	620
Community	310	310	310	310	310	310
R^2	0.1720	0.1709	0.1644	0.1565	0.1494	0.1436
Wald $\chi^2(2)$	273.53	234.77	205.53	183.31	166.12	152.53
Prob > χ^2	0.0000	0.0000	0.0000	0.0000	0.0000	0.0000

This table presents moral hazard tests using raw moment simulations based on Equation (9). All variables are in 2000 Indonesian rupiah. Random-effects approach is employed. Standard errors are reported in parentheses. Coefficients significant at the 10% level are denoted by *, at the 5% level by **, and at the 1% level by ***. *Source*: authors' calculation from IFLS dataset and BMKG.

Table 7. Moral hazard only regressions using IV-2SLS with Fixed Effects approach

	Consumption moment					
	(1)	(2)	(3)	(4)	(5)	(6)
γ value	1.00	1.20	1.40	1.60	1.80	2.00
Average log of previous income	0.205*	0.249*	0.289*	0.327	0.362	0.396
	(0.103)	(0.123)	(0.145)	(0.168)	(0.191)	(0.215)
Observations	620	620	620	620	620	620
Community	310	310	310	310	310	310
R-sq	0.476	0.507	0.520	0.523	0.520	0.514
adj. R-sq	-0.054	0.008	0.035	0.040	0.034	0.021
$F-$statistics	53.90	59.33	62.93	64.99	65.98	66.32
$p-$value	0.000	0.000	0.000	0.000	0.000	0.000
Kleibergen-Paap rk LM statistic	15.576	17.793	19.708	21.286	22.558	23.572
$\chi^2(3)$ $p-$value	0.0004	0.0001	0.0001	0.0000	0.0000	0.0000
Cragg-Donald Wald F stat.	7.050	7.768	8.357	8.824	9.188	9.471
Kleibergen-Paap rk Wald F stat.	5.467	5.998	6.483	6.897	7.239	7.518
Hansen J statistic	0.487	0.436	0.379	0.328	0.285	0.250
$\chi^2(2)$ $p-$value	0.4855	0.509	0.5380	0.5668	0.593	0.6173

This table presents moral hazard tests using raw moment simulations based on Equation (9). All variables are in 2000 Indonesian rupiah. Instruments used in this estimation are average of ADLs, and rainfall in the previous year. Robust IV-2SLS estimations with fixed-effects are employed. Standard errors are reported in parentheses. Coefficients significant at the 10% level are denoted by *, at the 5% level by **, and at the 1% level by ***. *Source*: authors' calculation from IFLS dataset and BMKG.

Table 8. Limited commitment only regression

	Consumption ratio				
	(1)	(2)	(3)	(4)	(5)
Consumption ratio in the previous wave	0.0621***	-0.920***	-0.919***	0.0694*	-0.902***
	(0.0325)	(0.00758)	(0.00659)	(0.0353)	(0.00769)
Join Rosca =1	-0.0290	0.162	0.196*	0.307***	0.189*
	(0.189)	(0.0902)	(0.0831)	(0.0844)	(0.0955)
Rosca × Lag of cons. ratio	0.187**				
	(0.0876)				
Constant	1.057***	2.172***	2.240***	0.961***	2.231***
	(0.0699)	(0.0177)	(0.0281)	(0.0450)	(0.0304)
Observations	6016	6016	6016	6016	6016
Households	3008	3008	3008	3008	3008
R^2 (within)	0.6158	0.833	0.875	0.006	0.886
Wald χ^2	13.94				
p-value	0.0030				
F-stat		7368.19	787.39	17.41	58.68
p-value		0.00	0.0000	0.0000	0.0000
Interaction-terms	4.54				3.51
p-value	0.0332				0.0000
Estimation method	RE	FE	FE	OLS	FE
Fixed effects	No	Household only	Household, community, and wave	Household and wave	Community×wave

All variables are in 2000 Indonesian rupiah. Standard errors in parentheses. Clustered-robust error is employed in Column (1) and (4). Interaction-term statistics for Column (1) and (5) is $\chi^2(1)$ and $F-$statistics respectively. Coefficients significant at the 10% level are denoted by *, at the 5% level by **, and at the 1% level by ***. *Source*: authors' calculation from IFLS dataset.

Figure 1. The averages of community consumption and income.

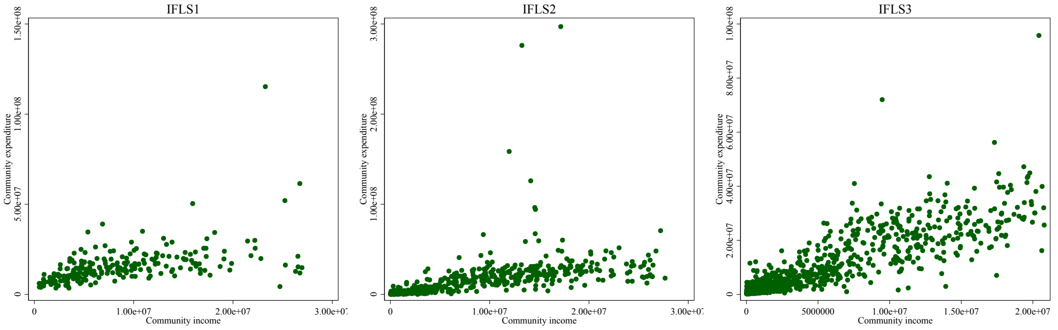

Figure 2. The residuals of consumptions and income.