Role of Background Risk and Social Health Insurance in Informal Credit Markets

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Abstract

This paper examines whether the introduction of Askeskin, a social health insurance program instituted by the Indonesian government, impacted investments in arisans - an informal, community-based credit association. The uncertainty in the timing of the payoffs in an arisan makes it an inherently risky investment. Our objective is to examine the impact of the social health insurance program on participation and investment in arisans.

Theoretically, in a model with health shocks, we show that the introduction of Askeskin, by lowering background risk, can result in greater investments in arisans. Empirically, using data from the Indonesian Family Life Survey, we find that access to Askeskin led to higher likelihood of participation and larger monetary investments in arisans - an effect that was primarily channeled via lower levels of background risk. Overall, our findings suggest that Askeskin affects participation in arisans through its impact on background risk.

JEL classification: I13, D81, O16, O17

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1. Introduction

This paper explores the impact of the introduction of Askeskin program, a subsidized social health insurance for the poor and informal sector workers, instituted in 2005 by the Indonesian government, on the likelihood of committing to a risky investment. In particular, we focus on investments in *arisans* – an inherently risky informal community-based Rotating Savings and Credit Association (ROSCA)[1]. Unexpected medical expenditures constitute a major source of background risk for many households in developed and developing countries and could potentially impact the amount of investment in risky financial assets. The provision of social health insurance could alter this dynamic by shielding the households from unanticipated health expenditures, thereby possibly altering their appetite for risk. Our work exploits the interplay between social health insurance, background risk, and risk aversion in explaining participation in arisans.

In a ROSCA, a group of individuals meet periodically, voluntarily pool in their savings and this "pot"of savings is then disbursed to one of the members. Once a member has received a pot, she is ineligible to receive another one. The ROSCA ends once each member has received exactly one pot. The order of disbursement of the pooled funds amongst the members is determined either by lottery or bidding, termed as random ROSCA and bidding ROSCA, respectively.

Following the seminal work by Besley *et al.* (1993), we take the view in this paper that ROSCAs are largely used to purchase indivisible goods. While ROSCAs, especially the bidding variants are suitable for risk hedging and risk sharing (Calomiris & Rajaraman, 1998; Klonner, 2003), the arisan in Indonesia is in general a random ROSCA where interest is predominantly not calculated (Varadharajan, 2004). We take the view that ROSCAs are risky sources of finance; risk arises either because of the failure in commitment of a member to pay into the ROSCA after they have won the pot or due to the uncertainty in the timing of the payoffs, which makes the ex-post real rate of return on ROSCAs stochastic. Yet, the probability of winning the pot of a random ROSCA is unlikely to be related with other sources of risk including health shocks systematically, and demographic characteristics of the participants, which makes it an ideal bed to test our model predictions.

In order to understand risk arising out of the uncertainty in the timings of payoffs, con-

[1] In the rest of the paper, we will use the word arisan and ROSCA interchangeably.

sider the case of a household that wishes to finance an indivisible investment opportunity using an arisan. Typically, ROSCAs allow participants to obtain the indivisible goods earlier than autarky savings, which improves the ex-ante welfare of participants under imperfect financial markets. However, the timing of winning pot is uncertain and, ex-post, life-time return of ROSCAs depends on it. Therefore, the participants will perceive the return of ROSCAs being stochastic even when the nominal return of ROSCAs is constant and the default risk is absent. (see also Besley *et al.* (1993, 1994); Kedir *et al.* (2011))

How does the introduction of a social health insurance program impact participation in these informal credit markets? The literature has tried to explain participation in the ROSCAs by focusing largely on the role of credit constraints and poverty and the desire of individuals to purchase indivisible goods such as consumer durables or investment goods. ROSCAs were identified as a commitment device to facilitate savings, and work as community-based informal insurance. We complement this literature by exploring the impact of a social health insurance program on an individual's decision in participating in arisans, through the lens of background risk.

Our theoretical model extends the seminal work of Gollier & Pratt (1996) to include social health insurance. Their paper shows that the introduction of an unfair background risk to wealth makes agents more *risk vulnerable* in the sense that it makes a risk averse agent to behave in a more risk averse way towards any other independent risk. Background risk in our model arises due to expectations of contingent out-of-pocket medical expenditure. In the absence of health insurance, the background risk causes agents to become more risk vulnerable and exhibit more risk averse behaviors. This in turn induces them to hold a lower proportion of their savings in the form of risky assets.

The introduction of health insurance reduces or completely removes unexpected out-of-pocket health expenditure and consequently lowers background risk, leading to an increased demand for risky assets. Interestingly, the effect of health insurance on investment in the risky assets is stronger in the case of social health insurance. Essentially, access to social insurance not only lowers background risk but also increases household wealth by the subsidized premium. This additional wealth effect serves to further increase the holding of risky assets in an individual's portfolio. Our theoretical results therefore imply that the introduction of a social insurance program such as Askeskin could potentially lead to an increase in participation in arisans - the risky asset in our setup. Importantly, this effect of health insurance on participation in arisans is mediated by background risk.

We empirically test the validity of our theoretical predictions using data from two rounds of the Indonesian Family Life Survey (IFLS) and consistent with our theory, our empirical results suggest that the provision of social health insurance increases participation in arisans. Moreover, the provision of social health insurance also reduces the individual's background risk (as measured by our empirical proxy - observed risk aversion). More specifically, when we use the observed risk aversion as an outcome variable, we find individuals with Askeskin coverage had greater chance of transitioning into the lower risk averse categories. Importantly, after controlling for background risk, the possession of Askeskin does not have an independent effect on the extensive margin of arisan participation or on monetary investments in arisans.

This paper is connected to several strands of the literature. There is a rich literature in macroeconomics and finance that has explored the impact of uninsurable income risk on individual savings, portfolio allocations and asset prices. The presence of such uninsurable labor income risk could trigger precautionary savings (Kimball, 1990) or change the pattern of human capital accumulation (Levhari & Weiss, 1974). Further, the impact of such a risk on portfolio choice has also been explored by a few studies (Merton (1971); Kimball (1993); Constantinides & Duffie (1996); Heaton & Lucas (1996, 2000)). A related strand of literature points out the importance of ROSCAs as a portfolio choice in developing countries. Particularly, for women, ROSCAs serve as an avenue to protect their savings from immediate consumption by men and help in empowering them financially (see Anderson & Baland (2002), Johnson (2004)). Our work here complements this literature by emphasizing the role of social health insurance in mitigating background risk, arising out of uncertain health expenditure. Due to lower background risk, prevailing channels for savings are utilized more effectively.

Our work adds to the emerging literature that has sought to examine the impact of social health insurance on portfolio choice. While there is a fairly large literature that examines the link between portfolio choice and health status (See Rosen & Wu (2004) and Edwards (2008)), the literature on the impact of social health insurance on portfolio choice is limited. Ayyagari & He (2016) use the exogenous reduction in prescription drugs caused due to the introduction of Medicare Part D in 2006, to test the effect of medical expenditure risk on household portfolio choices for elders in the United States. In related work, Angrisani *et al.* (2018) examine whether access to Medicare increases investments in risky assets for senior citizens in the United States. These papers find senior citizens with access to social health insurance increase their holdings of risky assets in their portfolios. We build on this literature by trying to understand the implications of social insurance on participation in informal credit markets in the context of a developing economy. Importantly, distinct from the above papers, we emphasize the role of background risk in understanding the impact of social health insurance on portfolio choice.

Finally, this paper also relates to a small but important literature that studies the extent to which introduction of a social insurance program affects other private formal and informal sources of credit and insurance. In the absence of access to formal insurance markets, households in developing economies are known to rely on community-based support networks to cope with the adverse impact of health shocks. It is therefore important to investigate whether such social health insurance programs simply displace or "crowd out" informal community-based credit mechanisms.

Cox *et al.* (1998), Attanasio & Rios-Rull (2000) and Jensen (2004) conclude that an increase in the benefits from public transfer programs crowds out private transfers which were used to support extended family members. More recently, Liu (2016), who examines the impact of a large-scale social health insurance program implemented in China, concludes that the program was welfare enhancing as it reduced the use of costly self-insurance mechanisms. Lehr (2016) also finds a positive benefit to social insurance, despite agents insured privately, and attributes such benefit to a re-distributive effect.

The results of our paper suggest that the introduction of the Askeskin program "crowded in" participation in informal credit markets. Our results are robust to two techniques that allay concerns on possible endogeneity of targeted social insurance. An inverse-probability weighted adjustment to the data, does not change our main results. Additionally, following the procedure laid out in Oster (2019), we also check for coefficient stability of our main results, under the condition of proportionate selection into social insurance based on observed and unobserved controls.

The rest of the paper is structured as follows: Section 2 sets up the model. We discuss our dataset, key variables in Section 3 and empirical strategy in Section 4. Section 5 describes our empirical results. Finally, Section 6 contains the concluding remarks.

2. The Model

In this section, we extend Gollier & Pratt (1996)'s model (GP from now) with *background risk* to examine optimal investment in a risky asset in the presence of health risk and social health insurance. Our objective is to understand how access to social insurance will impact investment in arisans.

Next, we introduce the notion of "*risk vulnerability*" which proves crucial to understanding the impact of background risk on portfolio choice. Consider a decision maker who has a von Neumann-Morgenstern utility function u which is twice differentiable, $u' > 0$ and $u'' \leq 0$. Let us define an indirect utility function given by

$$v(x) \equiv E[u(x + \tilde{e})] \tag{1}$$

where $\tilde{e}$ denotes a background risk. As demonstrated in GP, understanding the impact of the background risk on the optimal investment in independent risk is equivalent to examining the consequences of the change in preferences from u to v. Put differently, the portfolio choice of an individual with preferences u with background risk would be equivalent to the portfolio choice of an individual with preferences v. GP introduce the weakest conditions on preferences which guarantee that adding an unfair background risk to wealth makes risk-averse individuals behave in a more risk-averse way with respect to another independent risk. If satisfied, this restriction which they term as *risk vulnerability* would mean that an individual's willingness to bear risks is vulnerable to the introduction of another unfair risk. Formally, for any von Neumann-Morgenstern utility function u, this restriction can be written as

$$-\frac{v''(x)}{v'(x)} = -\frac{E[u''(x + \tilde{e})]}{E[u'(x + \tilde{e})]} \geq -\frac{u''(x)}{u'(x)} \tag{2}$$

for all x where $E[\tilde{e}] \leq 0$. Given (1), this condition is equivalent to

$$r_v(x) \geq r(x) \tag{3}$$

where $r_v(x) = -v''(x)/v'(x)$ is the the absolute risk aversion for the indirect utility function v and $r(x) = -u''(x)/u'(x)$ is for the direct utility function u.

Equation (3) implies that the presence of non-positive mean risk $\tilde{e}$ induces individuals to behave in more risk averse manner. This risk vulnerability condition holds true for all HARA utility functions. We make use of this condition in our model below to understand the impact of health insurance on risky savings. Next, we provide a brief description of our model which extends the GP framework to include access to social insurance.

2.1 Baseline model without insurance

In this section, we discuss our baseline model where the individual has no access to medical insurance. Consider an individual endowed with initial wealth a and health-human capital, H, which is subject to an adverse health shock, $\tilde{\delta} \geq 0$. In particular,

$$\tilde{\delta} = \begin{cases} 0, & \text{with probability } 1-p \\ \delta > 0, & \text{with probability } p \end{cases}$$

The individual can restore the health capital using medical service m, up to the initial level, H, i.e. $\tilde{m} \leq \tilde{\delta}$. The cost of providing these medical services is $f(m)$ and we assume $f(0) = 0$, $f' > 0$, and $f'' > 0$. The health-human capital available for the labor market is therefore stochastic and is given by

$$\tilde{H} = H - \tilde{\delta} + \tilde{m} \tag{4}$$

Labor is supplied inelastically and each unit of $\tilde{H}$ earns the wage rate of w. Hence, the total labor income is $w\tilde{H}$. Although the wage rate is non-stochastic, the labor income is stochastic due to stochastic human capital. The household has an access to risky savings opportunity, which offers the gross real rate return of $1 + \tilde{r} \geq 1$, and a storage technology which pays one unit per each unit of savings. The price of risky asset is normalized to unity. We assume $corr(\tilde{r}, \tilde{\delta}) = 0$, implying that health shocks are independent of the return on risky assets, thus savings in the risky asset cannot insure the health risk. This assumption is reasonable in our context because it is unlikely that the outcome of the arisan lottery and the future health risk of the participants are systematically correlated. The budget constraint of individual can be written as

$$\tilde{c} \leq (1+\tilde{r})s + (a-s) + w\tilde{H} - f(\tilde{m}) \tag{5}$$

where $\tilde{c}$, s and $a-s$ denote consumption, the amount saved in the form of risky assets and the amount allocated to risk free storage, respectively. The individual maximizes the expected utility of the consumption based on preference $u(c)$, which satisfies the risk vulnerability condition (2). The Lagrangian for utility maximization is

$$\max_{\{m,s\}} L = E[u(\tilde{r}s + a + w[H - \tilde{\delta} + \tilde{m}] - f(\tilde{m})) + \mu\{\tilde{\delta} - \tilde{m}\}]$$

The first order condition for interior optimum concerning the portfolio choice is

$$E[\tilde{r}u'(\tilde{c}^o)] = 0 \tag{6}$$

where $\tilde{c}^o$ is the optimal consumption under the baseline case with no insurance. The optimality condition for the demand for contingent health expenditure is

$$\tilde{m^*} = \min[f'^{-1}(w), \tilde{\delta}]. \tag{7}$$

Given (7), the solution for consumption with no insurance is given by

$$\tilde{c}^o(s) = \begin{cases} \tilde{r}s + a + w[H - \delta + m^*] - f(m^*), & \text{with probability } p \\ \tilde{r}s + a + wH, & \text{with probability } 1-p \end{cases} \tag{8}$$

where $m^* = \min\{f'^{-1}(w), \delta\}$ denotes the optimal medical service demand if $\tilde{\delta} = \delta$. When the amount of risky investment is optimal, s satisfies (6).

2.2 Model with insurance

Now consider an actuarially fair insurance program. It provides m^* in the case of health shock, $\tilde{\delta} = \delta > 0$ in exchange for an upfront payment of insurance premium of $pf(m^*)$. Analogous to (6), the Euler equation is given by

$$E[\tilde{r}u'(\tilde{c}^m)] = 0 \tag{9}$$

The consumption under an actuarially fair insurance is therefore given by

$$\tilde{c}^m(s) = \begin{cases} \tilde{r}s + a + w[H - \delta + m^*] - pf(m^*), & \text{with probability } p \\ \tilde{r}s + a + wH - pf(m^*), & \text{with probability } 1-p \end{cases} \tag{10}$$

where s satisfies (9) at optimum.

Next, we compare risky savings under the no insurance case with the insurance case. Our main result can be summarized in the proposition below.

Proposition 1 *The introduction of health insurance reduces background risk arising from expected health expenditure. This in turn raises the size of the optimal investment in risky assets.*

In order to see how the introduction of health insurance impacts savings in the risky asset, notice that $\tilde{c}^o$ is a mean preserving spread of $\tilde{c}^m$ for a given value of s. Using (8) and (10), we can rewrite the consumption with no insurance $\tilde{c}^o(s)$ as

$$\tilde{c}^o(s) = \tilde{c}^m(s) + \tilde{e} \tag{11}$$

where

$$\tilde{e} = \begin{cases} -(1-p)f(m^*) & \text{if } \tilde{\delta} = \delta \text{ with probability } p \\ pf(m^*) & \text{if } \tilde{\delta} = 0 \text{ with probability } 1-p \end{cases} \tag{12}$$

Note that $E\tilde{e} = 0$. Let s^o and s^m denote the optimal amounts saved in the form of risky assets under no insurance and the actuarially fair medical insurance, respectively. In order to determine the relative size of s^o and s^m, we combine (6), (9) and (11) to obtain the following condition:

$$0 = E[\tilde{r}u'(\tilde{c}^m(s^o) + \tilde{e})] = E[\tilde{r}u'(\tilde{c}^m(s^m))] \tag{13}$$

Using the fact that $corr(\tilde{r}, \tilde{\delta}) = 0$, we can rewrite the above expression as

$$0 = E[\tilde{r}v'(\tilde{c}^m(s^o))] = E[\tilde{r}u'(\tilde{c}^m(s^m))] \tag{14}$$

for some indirect utility function v, satisfying (1). Under the risk vulnerability condition (2), since an individual with preferences v is more risk averse than an individual with preferences u, it follows that $s^o < s^m$ (see appendix (A.1) for the formal proof). Put differently, the demand for risky assets under no insurance must be no greater than that under an actuarially fair insurance. Essentially, the presence of uninsured health expenditure plays the role of increased background risk, $\tilde{e}$. The possibility of paying health-related expenses adds a mean-zero fluctuation in consumption, relative to the actuarially fair insurance case. This increases observed risk aversion by (2) and reduces demand for risky assets.

2.3 Model with social insurance

In this section, we examine the savings in the risky asset when there is access to a social insurance program. Specifically, we compare the optimal savings in the risky asset under social insurance with that obtained under an actuarially fair insurance policy. Our main result is summarized in the Proposition below.

Proposition 2 *The observed risk aversion is lower under social insurance than in the actuarially fair insurance case. As a consequence, savings in the risky assets is greater with access to social insurance.*

To see this, consider the case where the government subsidizes $1-q$ fraction of the insurance premium $(1 > q > 0)$. It follows from (11) and (12) that the consumption under this social insurance regime can be written as

$$\tilde{c}^o(s) = \tilde{c}^a(s) + \tilde{\eta} \tag{15}$$

where $\tilde{c}^a$ is the consumption under the social insurance program and $\tilde{\eta}$ is given by

$$\tilde{\eta} = \begin{cases} -(1-pq)f(m^*) & \text{if } \tilde{\delta} = \delta \\ pqf(m^*) & \text{if } \tilde{\delta} = 0. \end{cases} \tag{16}$$

Interestingly, combining (12) and (16), we find $\tilde{\eta} = \tilde{e} - p(1-q)f(m^*)$, implying that the social insurance not only removes the background risk but also effectively increases household wealth by the subsidized premium $p(1-q)f(m^*)$. This additional wealth effect serves to reduce risk aversion relative to the actuarially fair case. Formally, the ranking of the measured relative risk aversion under the three regimes is given by

$$RA_o(x) = \frac{r_v(x)}{x} > RA_m(x) = \frac{r(x)}{x} > RA_a(x) = \frac{r(x)}{x + p(1-q)f(m^*)}$$

where RA_o, RA_m and RA_a denote the coefficient of relative risk aversion under no insurance, actuarially fair insurance and subsidized social insurance regimes, respectively. Therefore, we expect that the effect of the social insurance on risky savings *may* be larger than that of actuarially fair insurance because of lower observed relative risk aversion under the social insurance. To summarize, the presence of an additional wealth effect in the case of the social insurance makes investors behave in a less risk averse manner, which may induce individuals to save more in the form of the risky asset when compared to the actuarially fair case.

3. Data and variables

The analysis in this paper is based on the Indonesian Family Life Survey (IFLS), a nationally representative longitudinal panel consisting of data on individuals, households and community facilities. Our analysis is based on two rounds of IFLS, namely the fourth and the fifth round conducted in 2007 and 2014 respectively. For the purpose of our analysis, we restrict the sample to individuals who are of age 15 years or above, since only this subset of individuals was inquired about their participation in arisan and are enquired about their risk preferences.

The sample size in IFLS rose each consecutive round as new households entered the sampling frame formed by split-offs from existing households or due to inclusion of new households in the sample. Within households, children turned into young adults over the course of time and new individuals were added to households due to marriages, etc. Our final sample size is 43,618 individual-year observations over the two waves. Summary of the information about the sample is listed in Table 1. In the subsections below we discuss the construction of main variables used in the analysis.

Outcome variables - Participation in Arisan: The objective of our analysis is to examine the impact of the Askeskin program on participation in arisans. We consider three measures of arisan participation in our sample data. First, we measure the decision of participation in arisan at the extensive margin, and assign an indicator variable (Yes (1) or No (0) decision). Second, we measure the household participation in total number of arisans in the recall period of the past 12 months, which is the intensive margin. Third, we also measure the annual monetary contributions to arisans (in logarithm terms).

Table 1 lists the average arisan participation and monetary contributions by adults. Around 22 percent of adults participate in an arisan. Of them, women are twice as likely to participate than men. These programs are more frequently used by rural as compared to urban households and there are provincial disparities. Among arisan participants, the median level of participation is one arisan per year. On average, annual monetary contributions towards arisan amount to about one-tenth of household monthly consumption (per capita nominal rupiah terms) or about 7.5 percent of monthly labor income. One fact that motivates this study is that the average number of arisan engagements rises over time and nominal monetary contributions rise by close to 90 percent between wave four and five of IFLS.

Social Health Insurance - Askeskin: *Askeskin*[2], a social health insurance rolled out in 2005 by the Indonesian government in 2005 provides an interesting setting to study how large-scale public safety nets impacted household decisions in a developing country seting. This program was intended to provide health insurance coverage to an estimated 60 million poor households and informal sector workers, who previously had no cover. The entire premium, of 6000 Rupiah per capita, was paid by the state on behalf of the beneficiaries. Health service fee was waived off when services were accessed in public hospitals public hospitals, community health centres (Puskesmas) and village clinics. Outpatient medical consulting, procedures, pregnancy check-ups, deliveries and family planning related counselling was provided. Inpatient services at public and private facilities, ambulatory services for public facilities and a comprehensive set of conditions were covered. Some procedures like cosmetic surgery, physical check-ups, alternative medicine, dental prostheses and fertility treatment were not covered.

Askeskin eligible beneficiaries were targeted for enrollment in a two-step process. In the first step, Indonesia's statistics agency conducted a country-wide poverty census to prepare

[2]Asuransi kesehatan keluarga miskin - Bahasa Indonesian for Health insurance for poor families

a proxy means test based on 14 asset indicators, so as to categorize households as poor or vulnerable to being poor (see Sim *et al.* (2015)). Based on this census, district-wise quotas of *poor* (living below the consumption poverty threshold of a district) or *near poor* (vulnerable to poverty and have consumption below 1.5 times the district threshold) households were drawn up. In the second-step, districts had to validate or verify poverty status. Districts differed in carrying out this exercise; some sent field staff to verify the asset status and others estimated household per-capita consumption based on their own survey (Sparrow *et al.* (2013); Harimurti *et al.* (2013)).

Askeskin roll-out should have exclusively targeted poor districts first. So, a study could have utilized cross-district comparison of intended beneficiaries (poor and near poor families). But rapid expansion of Askeskin, prior to 2007 and between IFLS waves (2007 and 2014) does not allow us to leverage the district-level variation in insurance status. For example, when districts are ordered into quantiles based on district-level percentage of poor people (as per first-stage quotas), 21 percent of poorest district individuals and 14 percent of individuals in the richer districts had already gained Askeskin by 2014. So, instead, we use the within individual variation in Askeskin coverage over time to help identify the effect of Askeskin on participation in arisans. This individual fixed effects identification strategy is crucial, also, to remove the confounding effect of unobserved idiosyncratic risk aversion (r_i) traits (explained later in Section 4 in eq (18), so as to know the impact of *background risk* on risky savings. Further, our confidence in the fixed effects strategy is bolstered when addition of time varying individual, household and community covariates, does not alter the main findings of the study.

We use self-reported possession of Askeskin insurance cover (Yes=1 or No=0 indicator) as the explanatory variable. Table 1 presents summary statistics of the gradual proliferation of Askeskin insurance within the IFLS sample. Prior to IFLS 4, there was no Askeskin-based health insurance cover. However, by 2007, close to 12 percent of adults had Askeskin insurance, and by 2014, Askeskin coverage had doubled, to cover 24 percent of the adults in the sample.

Observed risk aversion (r_{it}^{obs}): Risk preferences are surveyed for Indonesian adults in the IFLS 4 and 5 survey rounds. The respondents are asked a sequence of questions, wherein at each step they who choose between a pair of hypothetical lottery choices. The options may be termed as 'risky' or 'safe' choice, (a modified multiple price list, following Holt & Laury (2002)). The 'risky' payoff is based on an equal chance of winning or losing some money, vis-à-vis, the 'safe' option which always has a certain payoff. If respondents choose a risky option, they proceed to answer a further question on a different lottery, where, the gain and loss are much higher than that of the previous question, thus making his choice more risky. Here, riskiness of a choice is determined by the coefficient of variation of the lottery (CV from now, $\text{CV} = \frac{\text{Standard Deviation}}{\text{Expected value}}$) . The sequence of questions continues until the individual declines to choose a risky payoff and instead chooses a certain payoff.

In essence, the questionnaire elicits risk aversion by seeing how far an individual will go in terms of accepting a risky payoff. For example, a respondent must choose between Option 1 which pays 800 Indonesian rupiah (IDR) with certainty and Option 2 which pays either 400 or 1600 IDR with equal chance. In option 2, the expected value (EV) of the gamble is 1000K and standard deviation is 600K, thereby giving CV = 0.6 and making it riskier than option 1. The higher the CV of the choice made, the lesser risk averse is an individual.

We order the individuals into five ordinal categories of risk aversion based on the respondent's answer to the hypothetical lottery, with 0 representing 'least risk averse' individuals, and 4 representing 'extremely risk averse' individuals. A higher ordinal value implies that an individual is more risk averse. Figure 1 depicts an outline of the questions and the categorization exercise which assigns an *observed risk aversion* rank to each individual in the sample. Most number of individuals were categorized as being 'extremely risk averse', i.e. they choose the safest option with no gain and no loss, followed by 'very risk averse' category. The median risk aversion category, however, had the lowest number of adults in both waves.

More importantly, between the survey waves, the proportion of individuals classified as belonging to the least observed risk averse category ($r_{it}^{obs} = 0$) rises from 14.51 percent to 19.32 percent. The proportion of individuals classified under the two lowest levels of observed risk aversion increases from around 22 percent to about 32 percent. Figure 2 corroborates this point. Furthermore, in the sample, there is substantial transition between observed risk aversion categories for the same individual over time. Among people classified as 'extreme averse' in 2007, about 18 percent report being in the 'least risk averse' category by 2014. In summary, the sample characteristics seem to indicate that post-implementation of Askeskin, there is a transition of individuals towards lesser observed risk aversion, the reasons for which we will explore in the subsequent section.

Health Shocks In addition to the above key variables, we also use shocks to health status to explain our outcome variables. Since a large component of health status is not randomly distributed but rather directly related to the dietary and healthcare choices made, we attempt to use an exogenous measure of health status. As a measure of health shock, we use the changes in an index of Activities of Daily Living (ADL) between one survey period and the next, a metric already employed in Indonesia by Gertler & Gruber (2002). Our approach to measuring a health shock is described in more detail in appendix (A.2).

4. Empirical Strategy

Our theory developed in the previous section yields the following testable hypotheses:

Proposition 3 (Testable hypotheses)

1. *The provision of social insurance increases the demand for risky assets, by removing the background risk.*
2. *Once we control for background risk, the estimated effect of social insurance would be lower.*
3. *Social insurance may have stronger impacts on the risky savings than other insurance.*

Empirical Model for Risky Savings

To test aforementioned hypotheses, we formulate the following empirical model:

$$S_{it} = \alpha_0 + \alpha_1 INS_{it}^{\text{Askeskin}} + \alpha_2 b_{it} + \alpha_3 INS_{it}^{\text{Others}} + \beta_1 r_i + \beta_2' X_{it} + \tau_t + v_{it} \tag{17}$$

where S_{it} denotes risky savings of an individual i at time t and INS_{it}^{X} denotes the membership status of insurance X, which takes value of 1 if she is a member and zero otherwise. The variable b_{it} is a measure of time-varying background risk, r_i denotes her absolute risk aversion, and X_{it} are time-varying covariates such as health shocks, age, education level, urban or rural residence indicator, healthcare supply in the community, family composition[3] and total family consumption (a proxy for earnings); τ_t captures wave-specific fixed effects. However, the problem with estimating eq (17) is that no direct measure of b_{it} is available. If b_{it} is excluded from the model, coefficient on social insurance, α_1, is upward biased and $\alpha_1 > 0$ as it would capture the effect of omitted background risk.

Based on our theory, we posit that observed risk aversion, r_{it}^{obs} comprises time-varying background risk b_{it}, and time-invariant risk aversion:

$$r_{it}^{obs} = b_{it} + r_i. \tag{18}$$

Here, we take that r_{it}^{obs} corresponds to $r_v(x)$ and r_i to $r(x)$ in eq (3). With eq (18), our estimating equation (17) becomes:

$$S_{it} = \alpha_0 + \alpha_1 INS_{it}^{\text{Askeskin}} + \alpha_2(r_{it}^{obs} - r_i) + \alpha_3 INS_{it}^{\text{Others}} + \beta_1 r_i + \beta_2' X_{it} + \tau_t + v_{it} \tag{19}$$

In the presence of b_{it}, the estimated size of α_1 will become lower and $\alpha_2 < 0$. Furthermore, by construction, r_i is negatively correlated with b_{it} and S_{it}. Since, r_i is still unobservable, we expect an upward bias on α_2 when an OLS or random effects model is employed. To eliminate this bias, we introduce *individual fixed effects* that sweeps r_i out from eq (19). Finally, we expect $\alpha_1 > \alpha_3$, due to the wealth effect of social insurance.

Empirical Model for Background Risk

One of the predictions of our theoretical model is that the introduction of social health insurance results in lower levels of risk aversion by reducing potential background risk.

We develop a supplementary hypothesis which tests the key mechanism of our theoretical model:

$$b_{it} = \gamma_0 + \gamma_1 INS_{it}^{\text{Askeskin}} + \gamma_2 INS_{it}^{\text{Others}} + \gamma_3' X_{it} + \xi_{it} \tag{20}$$

[3]Household composition, especially, the presence of young children, was found to be an important determinant of investment in risky assets (see Love & Smith (2010)).

Combining equations (18) and (20), we get:

$$r_{it}^{obs} = \gamma_0 + \gamma_1 INS_{it}^{\text{Askeskin}} + \gamma_2 INS_{it}^{\text{Others}} + \gamma_3' X_{it} + r_i + \xi_{it} \tag{21}$$

which can be consistently estimated by individual fixed effects. We expect $\gamma_1 < 0$ and $\gamma_2 < 0$ in eq (21). But our theory does not have clear prediction about the relative magnitude of γ_1 and γ_2. We estimate (21) using a linear fixed-effects model. X_{it} is vector defined above.

4.1 Robustness Checks

Assessing coefficient stability under unobserved selection

Unobserved time-variant factors of a person can influence her decision to be enrolled in Askeskin. This can pose a challenge to the the individual-level fixed effects strategy employed in equation (17) by inducing selectivity bias on *Askeskin* coefficient, due to omitted unobservables.

Such concerns on selectivity bias of regressors, can be allayed by assessment of coefficient stability, under observed controls. A lack of coefficient stability, under additional controls is indicative of omitted variable bias. Further, such movements in coefficients, was intuitively thought to be informative about possible bias from unobserved controls. It is based on the idea that selection on observables X_{it}, can provide a useful guide to assess the selection based on unobservables.

However, some recent studies point out, that coefficient stability or its lack thereof, is not a convincing indicator of robustness, unless one accounts for the additional explanatory power of new controls (see Altonji *et al.* (2005); Gelbach (2016); Oster (2019)). Formalizing this idea, Oster (2019) has developed a method that accounts for coefficient changes along with changes to R-squared to assess coefficient stability and thereby selectivity bias. She suggests calculating a *bias-adjusted beta (β^*)* which can be retrieved using the following steps.

- First, consider, a model that explains an outcome (Y), on a single explanatory variable with no other controls. Say, $\mathring{\beta}$ and $\mathring{R}$ are the estimated beta coefficient and R-squared of the uncontrolled model.

- Next, run a regression of Y on explanatory variable in the presence of observed covariates (partial controls). Here, $\widetilde{\beta}$ and $\widetilde{R}$ are the beta coefficient and R-squared of the partial control model.

- One has to assume a hypothetical R_{max}, which is the highest R-squared that is attainable if the model accounts for all covariates (full model). Citing a randomized evaluation of economic evaluation studies, Oster (2019) suggests using $R_{\text{max}} = \text{Min}\{1.3 \times \widetilde{R}, 1\}$.

- Finally, one can assume a proportionately equal selection relationship, i.e., unobserved covariates induce the same selection as observed covariates, formally indicated by a coefficient of proportionality $\delta = 1$. This is a reasonable starting point, as the most important controls are generally controlled for, according to Altonji *et al.* (2005) and Angrist & Pischke (2010).

Formally, then, the *bias-adjusted beta (β^*)* is :

$$\beta^* = \widetilde{\beta} - \delta[\mathring{\beta} - \widetilde{\beta}] \left[\frac{R_{max} - \widetilde{R}}{\widetilde{R} - \mathring{R}} \right] \tag{22}$$

If one observes that the bias adjusted beta coefficient is not significantly different from that in the model with observed controls, one can conclude selection on unobservables is inconsequential.

Inverse Probability Weight Adjustment

From our baseline models, we expect to find a significant effect of Askeskin provision on both Arisan participation and background risk. However, the validity of these estimates depends on the assumption that Askeskin participation is conditional on the observable control variables and the individual fixed effects. More formally, the validity requires $Cov(INS_{it}^{\text{Askeskin}}, v_{it}) = 0$ in eq (19) and $Cov(INS_{it}^{\text{Askeskin}}, \xi_{it}) = 0$ in eq (21). But in reality, there might be time varying unobservable factors that confound the estimated effect. In this section, we address this concern by extending our empirical model.

We use the Inverse Probability Weighting Regression Adjustment (IPWRA) method. The estimates from IPWRA are doubly-robust, as it requires only one of the outcome and treatment models to be correctly specified (Wooldridge, 2007; Imbens & Wooldridge, 2009). In the first step, IPWRA estimates a probit model considering the treatment status as the outcome variable. Thus, for each observation, it generates a propensity score for being in the treatment group; let us denote the predicted probability as $\hat{P}(INS_{it}^{\text{Askeskin}} = 1|X_{it})$.[4] Then these propensity scores are used to generate the Inverse Probability Weights (IPW). For the treated group, $IPW_{it} = 1/\hat{P}(INS_{it}^{\text{Askeskin}} = 1|X_{it})$ and for the control group, $IPW_{it} = 1/(1 - \hat{P}(INS_{it}^{\text{Askeskin}} = 1|X_{it}))$. In other words, IPWRA weighs the observations that are less likely to be in their respective groups more heavily. In the second stage, the baseline outcome model is estimated using the weights in the regression.

5. Empirical Results

The main results of the study following the individual fixed effects specification in equation (19) are in Table 2. We presents results for three different outcomes - two of them reflecting the participation in the "risky"arisan (at the extensive and intensive margin) and a third one reflecting a monetary investment (annual monetary contribution) in arisans.

Column 1 of Table 2 presents the estimated impact of Askeskin on the probability of participating in an arisan. Our empirical model includes the covariates (shown in table footnotes), as well as individual (person-level) and year fixed effects. We do not include a measure for observed risk aversion in this specification. The results suggest that individuals who report Askeskin coverage have a 1.8 percentage point higher probability of participating in an arisan. The presence of a health shock, unsurprisingly, reduces participation in arisans. One standard deviation increase in the health shock reduces arisan participation by about 1.1 percent in relation to the sample average. Total per-capita monthly expenditure is included as a covariate to proxy for earnings. It has a positive and statistically significant effect on arisan participation.

In column 2 of Table 2, we now explicitly include a measure of background risk in the model. As highlighted in the empirical model in section 4, observed risk aversion (r_{it}^{obs}) is a reasonable proxy for background risk, when individual fixed effects are used. We observe that the point estimate on observed risk aversion is small, yet negative (-0.004), and significant at the 10 percent level. The positive coefficient implies that, the marginal effect on arisan par-

[4]The probit estimation with individual fixed effects may provide inconsistent estimates due to the incidental parameters problem (see Neyman & Scott, 1948). However, inclusion of the individual fixed effects is crucial for our identification strategy. Therefore, we employ the Mundlak version of fixed effects estimation in these models, where the fixed effects are expressed as a linear function of the means of the time-varying observable covariates (see Mundlak, 1978; Wooldridge, 2010).

ticipation is greater for less risk averse individuals than those in more risk averse categories. An individual fixed effects should potentially account for biases due to the non-inclusion of time invariant variables, it is possible that time-varying individual, household and community factors have a confounding effect on our estimates. To allay such concerns, we also control for additional controls which reflect time-varying factors such as an individual's age, education, family composition and income and health supply in a community, such as number of hospitals and community medical centers[5]. These additional controls do not alter, the point estimates (or the standard error) on observed risk aversion or on Askeskin.

Importantly, after introducing the measure of observed risk aversion, the coefficient on social health insurance falls from 0.018 to 0.011 and turns insignificant. This is consistent with the separation of background risk effect which may otherwise be subsumed into the point estimate on social health insurance (omitted variable bias). These results indicate that a decrease in background risk results in an increase in participation in arisans.

In column 4 of Table 2, we present results from a model that does not include an individual fixed effect. Instead, the individual specific component (r_i) is modeled as a random effect. We now find that the coefficient on observed risk aversion r_{it}^{obs} rises from -0.004 in the fixed effects model to 0.005 in the random effects model. This is consistent with our expectation from the empirical model. To understand this, note from equation (18), that the observed risk aversion is a noisy measure of background risk. It follows from our discussion on equation (19) that the use of observed risk aversion as a proxy for background risk would result in a downward bias in OLS/Random effects estimators due to unobserved individual-specific risk preference parameter r_i. This bias is eliminated if the individual fixed effects were used. Our results indicate that this is indeed the case. In Table 2, columns 5 to 8, we present results from a model that uses the number of arisans as the dependent variable. In column 6, which is our main empirical specification, we find that reduction in one unit of observed risk aversion improves participation in arisans by around seven percent in relation to the average[6]. The effect of social health insurance (Askeskin) on arisan participation while significant, is reduced by a hundred basis points relative to the model without background risk. The results are quite similar to the extensive margin results, and suggest that a decrease in background risk (prox-

[5]IFLS questionnaires, called *Kamades* collect detailed information on community infrastructure, such as schools, hospitals and industries, in each survey round.

[6]The point estimate is 0.026 which is 7.7% of 0.337, the average arisan participation rate in our sample (shown in footer of same table).

ied with observed risk aversion) results in increase in the number of arisans participated in an year.

In columns 9 to 12 of Table 2, we present the results on monetary investment in arisans. Here we find that social health insurance is associated with a 19.5 percent increase in contributions towards arisans (column 9), but the effect is halved (and not significant), once we control for an observed measure of risk aversion (column 10). The estimated coefficient on observed risk aversion is -0.058 and statistically significant as well (column 8). This suggests that a unit decrease in observed risk aversion, results in a 6 percent increase in monetary contributions to arisans. Finally, we note that the coefficient on risk aversion is higher in a specification that includes the individual fixed effect as opposed to a random effects model.

The wealth effect of social insurance, outlined in proposition 2, is demonstrated by controlling for 'other' insurance (col. 3). The coefficient on other insurance is insignificant and lower than Askeskin. Moreover, introducing social insurance does not affect the size of Askeskin coefficient. This is possibly due to very little correlation between 'social' and 'other' insurance possession status; and both insurances having an independent effect on arisan participation.

In Table 3, we employ a linear probability model following eq (21)to establish the channel through which social insurance impacts risky investments. We present results on the impact of social insurance on observed risk aversion using an individual fixed effects model. In column 1, one can note how social insurance affects transition in the observed risk aversion rank. The point estimate on Askeskin insurance is -0.081, which suggests that people who gain Askeskin insurance over time are likely to exhibit less risk averse behavior (observed risk aversion is an ascending scale) as compared to an uninsured person. Upon, controlling for other private insurance, this estimate is only slightly reduced to -0.073 and is yet significant. Other insurance also has a similar but less significant effect, consistent with our model.

In columns 2 and 3 of Table 3, we present results where the outcome is an indicator equal to 1 if the individual is classified as being either in the 'medium' or 'least' risk averse category. Estimates are based on a linear probability model with individual fixed effects. The point estimate on Askeskin in column 2 is 0.031 and statistically significant. This signifies that other things equal, access to Askeskin increases the probability of a person falling into the 'medium' or 'least' risk aversion group by 3.1 percentage points. Put differently, the provision of the

Askeskin card translates into an 12% increase in the proportion of individuals falling into the two lowest risk averse categories.[7]. When other insurance is added to the model, it does not qualitatively alter the impact of social health insurance.

5.1 Robustness - Assessing Coefficient Stability

We employ Oster (2019) technique to assess coefficient stability as a robustness check, discussed in section 4.1. In Table 4, we show the result of the bias adjusted beta calculation for our primary empirical specification discussed in equation (17). To begin with, in column 1, uncontrolled model (without observed controls) is employed. Later, controlled models (with observed controls in place) are evaluated by employing an individual fixed effects and time dummies specification for all outcome variables. On the other hand, in column 2, the uncontrolled and observed controls specification is estimated using a pooled OLS technique. Here, the uncontrolled model has no individual or time dummies. But the control model has both dummies, yet it is estimated with a pooled OLS model.

Here, one can contrast the changes to the coefficient on Askeskin on two aspects. First, when a model without controls can be contrasted with a model with time-varying observed controls. Two, within a particular model specification, one can observe, how Askeskin coefficient might change based on the estimation technique, i.e. panel fixed effects vis-ˋvis pooled OLS model.

The Askeskin coefficient for extensive and intensive margins of arisan participation and arisan contributions are 0.018, 0.039 and 0.195 respectively in the first column of Table 4. There is a commensurate rise in within R-squared when observed controls are introduced i.e. ($\widetilde{R} > \mathring{R}$). Importantly, the bias adjusted beta coefficient of Askeskin for all three outcomes (β^*), was no different from the simple fixed effects model with observed controls. So, one can note relative stability of the coefficients of the individual-panel fixed effects estimates and under proportionate selection assumption ($\delta = 1$), such stability will persist despite not accounting for unobserved selection.

In contrast, in a model without time and individual fixed effects (column 2 of Table 4), the bias adjusted coefficients are notably different from the estimated coefficients, declin-

[7] The point estimate 0.031 is 12% of 0.241, which, in turn, is the proportion of people classified as medium or least risk averse, in our sample (see footer in Table 3)

ing in magnitude, but retaining the sign. This implies that time and individual fixed effects are essential to explain selection into Askeskin insurance and not accounting for it induces selection bias.

Comparing the bias adjusted beta (β^*) with the controlled model within each column in Table (4), highlights the following. For a panel fixed effects strategy, the bias adjusted beta is no different from the model with observed controls. But, for a pooled OLS model, the bias adjusted beta is distinctly different from its respective observed controls model.

Therefore, one can infer from the coefficient stability test that our primary empirical strategy of fixed effects estimation with observed controls are robust to selection into social insurance based on unobservable characteristics.

5.2 Robustness - IPWRA results

The results from IPWRA analyses are provided in Table 5. The results follow the mundlak fixed effects version discussed in section 4.1. All the main results from our baseline models remain unchanged. Also, the treatment effects from IPWRA are larger in magnitude compared to the same from our baseline models. Therefore, the estimates suggest that, after adjusting for selection into insurance, social health insurance does have a positively significant impact on arisan participation and in fact serves to reduce background risk.

To summarize, our empirical estimates suggest that provision of Askeskin results in an increase in participation and investments in arisans, a result consistent with the theoretical predictions. More importantly, we establish that this increase in demand for risky assets is channeled through a decrease in the background risk that results from access to the Askeskin (social insurance) program.

6. Conclusion

What role does background risk play on the decision to invest in risky assets in a developing economy? The large-scale implementation of the social health insurance program Askeskin by the Indonesian government provides us with a natural experiment to examine this issue. Our paper investigates both from a theoretical and empirical stand-point how such a program might have altered incentives and impacted participation in informal community-based risk sharing arrangements called arisans.

On the theoretical front, we show that the introduction of social health insurance, by lowering expected health expenditure and hence background risk, incentivizes more investment in arisans. Consistent with these predictions, our empirical estimates suggest that a lower background risk contributed to a significant increase in participation in arisans at the intensive and extensive margins as well as in an increased monetary contribution to the arisans.

In summary, our findings have important implications for public policy relating to provision of social health insurance, especially in a developing economy. The reduction in background risk in the presence of the insurance program provides a strong rationale for public sector investment in provision of health insurance. The "crowding-in" of other informal community-based risk sharing arrangements suggests that these social insurance programs have beneficial spillovers which further justify greater investment in such programs. Finally, we note that large social insurance programs have been introduced in several countries. It may be tempting to test the robustness of our empirical findings using data from other contexts, assuming that the relevant data are available.

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A. Appendix

In this section, we provide proofs of the proposition and description of construction of the health shock variable.

A.1 Proof of Proposition

Note that $u'' < 0$ and $v'' < 0$. Therefore, in order to establish $s^o < s^m$, suffices it to show $E[\tilde{r}v'(c^m(s^m))] < 0$.

Let $\phi_y(x) = E[\tilde{r}y'(c^m(x))]$. Then the first order condition under the actuarially fair insurance can be written as below.

$$\phi_u(s^m) = E[\tilde{r}u'(c^m(s^m))] = \int\int ru'(c^m(s^m))dF(\delta)dG(r) = 0 \tag{A.1}$$

where $F(\delta)$ and $G(r)$ are the cumulative density function of $\tilde{\delta}$ and $\tilde{r}$, respectively. Given (13), there exists a strict concave function W such that $v(c) = W(u(c))$. Therefore,

$$\phi_v(s) = E[\tilde{r}W'(u(c^m(s)))u'(c^m(s))] = \int\int rW'(u(c^m(s)))\,u'(c^m(s))dF(\delta)dG(r) \tag{A.2}$$

Then the first order condition under no insurance (6) becomes

$$\phi_v(s^o) = 0$$

Now we evaluate the sign of (A.2) at s^m. First observe that, when r is larger, u' is smaller, and vice versa. According to (A.1), these opposing effects cancel out exactly for $\phi_u(x)$ at s^m, yielding $\phi_u(s^m) = 0$. Since $W' > 0$ and $W'' < 0$, when r is greater, W' is smaller and vice versa. In other words, W' puts more weight when $r < 0$, compared to the insured case. This means ϕ_v puts more (smaller) weight to smaller (larger) values of r than ϕ_u. Hence, it follows that $\phi_v(s^m) < 0$.

A.2 Data Appendix: Construction of the health shock variable

A raw score is assigned to each physical activity of daily living, based on a graded scale, namely the 'ease', 'difficulty' or 'inability' to do that activity, giving scores of 1, 3 and 5 respectively. For the purposes of this study, the activities include lifting a heavy load for 20 meters, sweeping a floor, walk 5km, drawing water from a well, ability to bow or kneel, ability to dress by oneself, standing from a sitting position (from a chair or a floor), going to a bathroom by oneself. A simple addition of the reported ratings for each physical activity would give a total score for each individual. An aggregate index is then built using a formula developed by Stewart et al. (1989).

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

This aggregate index will lie between a maximum of 1 if the individual has limitation in performing all ADLs and minimum of 0 if the individual performs all ADL with ease. In some sense this scale is a reverse scale. Also, in recent survey rounds IFLS 4 & 5, the number of self-rated physical ADLs surveyed were higher than those in IFLS 3. To maintain comparison of ADL index across survey years and more importantly, since our dependent variable is the change in ADL index from previous survey years, we only consider ADLs which were originally available in the first IFLS survey round (IFLS 1 (1993)) and continued to appear in further rounds to build the health shock variable.

Following Gertler and Gruber (2002), we define our health shock in each IFLS round as ($\Delta h_t = ADL_t - ADL_{t-1}$), where '$t$' is an index for the survey round. The first difference of the self-reported health shock would eliminate any idiosyncratic bias of an individual who might constantly over- or under-rate his/her self-reported health. By construction, our adverse health shock (limitation in ADLs) will have a positive value and any improvement in health will have a negative value for Δh. By definition, an extreme adverse health shock $\Delta h = 1$ occurs only if the individual loses the ability to perform all ADLs. We note that the majority of shocks are due to a partial loss of functionality ($\Delta h < 1$).

Figure 1: Eliciting risk aversion rank from lottery pair choices

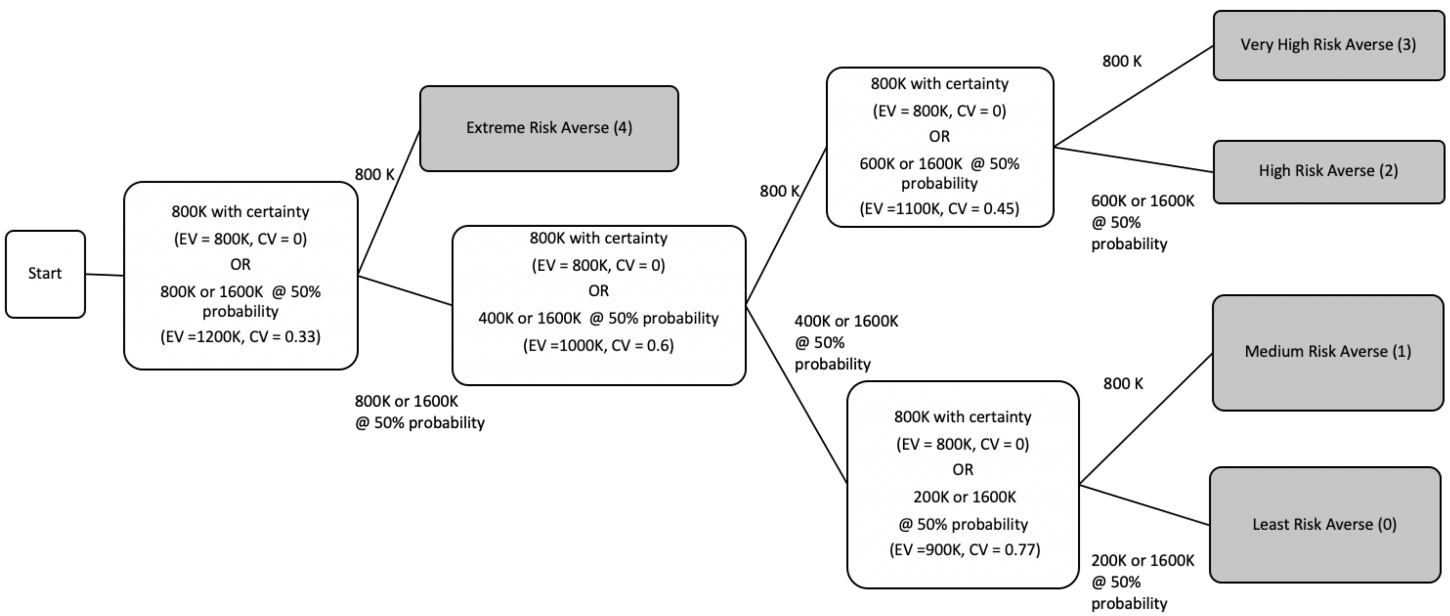

Figure 2: Risk aversion categorization of respondents

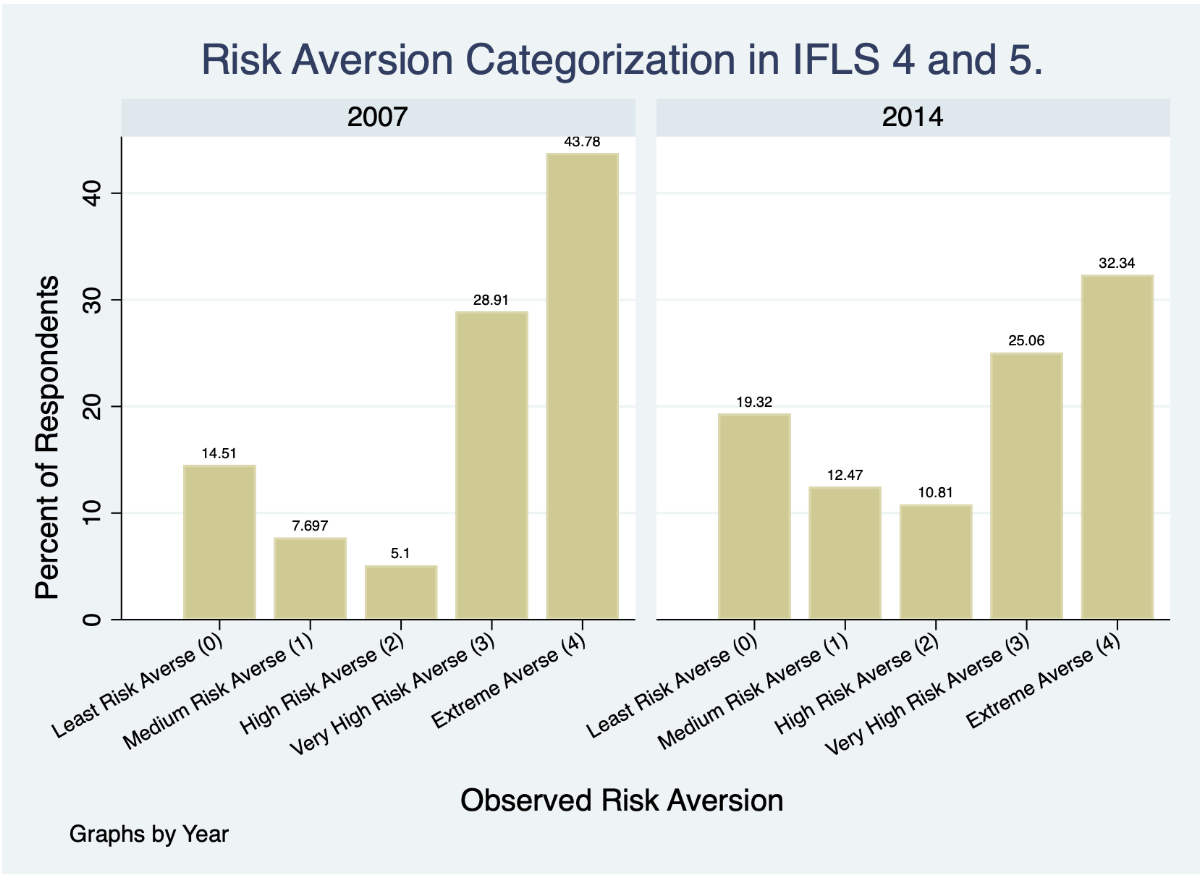

Table 1: Descriptive statistics (survey round-wise)

	(1) IFLS 4	(2) IFLS 5	(3) ALL
Demographic Information of Individuals:			
Individual's age (in yrs.)	39.86	41.17	40.52
	(17.53)	(17.38)	(17.47)
Health Shock(Δ ADL)	0.01	0.03	0.02
	(0.07)	(0.10)	(0.09)
Proportion of Sr.Citizens in family (Age≥ 50)	0.23	0.26	0.24
	(0.27)	(0.28)	(0.28)
Proportion of Adults in family	0.77	0.77	0.77
	(0.19)	(0.19)	(0.19)
Proportion of Female children in family ($0 < Age \leq 5$)	0.05	0.04	0.05
	(0.10)	(0.09)	(0.09)
Proportion of Male children in family ($0 < Age \leq 5$)	0.05	0.05	0.05
	(0.10)	(0.10)	(0.10)
Healthcare Supply:			
Number of hospitals in the community	3.52	5.61	4.58
	(3.27)	(4.29)	(3.96)
Number of community health centers	16.14	16.24	16.19
	(7.08)	(7.13)	(7.10)
Household Arisan Participation:			
Number of Arisans in an year	0.23	0.37	0.30
	(0.57)	(0.77)	(0.69)
Arisan Contribution (Log Rupiah)	2.06	2.94	2.50
	(4.43)	(5.21)	(4.86)
Household (HH) Consumption:			
Total Consumption Expenditure (Log Rupiah)	12.83	13.60	13.22
	(0.68)	(0.71)	(0.79)
Out of Pocket Medical Expense (Log Rupiah)	1.25	1.37	1.31
	(3.46)	(3.71)	(3.59)
Sample percentage- (Arisan & Health Insurance cover):			
Women in sample (%)	52.43	52.81	52.62
Individuals involved in Arisan (%)	18.03	25.05	21.60
Women involved in Arisan (%)	25.60	34.69	30.23
Men involved in Arisan (%)	9.70	14.27	12.01
Rural Area Households (%)	53.05	46.24	49.60
Individuals with Askeskin Insurance (%)	12.10	24.19	18.24
Other Health Insurance Holders (%)	0.17	0.92	0.55
Observations	21482	22136	43618

Table 2: Background risk and Arisan participation

	Arisan Participation (Extensive)				Number of Arisan (Intensive)				Arisan (Log Rupiah)			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Askeskin Insurance	0.018**	0.010	0.010	0.019***	0.038***	0.026**	0.025*	0.038***	0.195**	0.120	0.119	0.150**
	(0.008)	(0.008)	(0.008)	(0.005)	(0.012)	(0.013)	(0.013)	(0.009)	(0.094)	(0.099)	(0.099)	(0.064)
HealthShock	-0.099***	-0.089***	-0.089***	-0.120***	-0.176***	-0.169***	-0.169***	-0.198***	-1.374***	-1.138***	-1.138***	-1.230***
	(0.024)	(0.027)	(0.027)	(0.021)	(0.035)	(0.039)	(0.039)	(0.033)	(0.261)	(0.302)	(0.302)	(0.239)
Total Expenditure (Log)	0.037***	0.040***	0.040***	0.057***	0.081***	0.094***	0.094***	0.090***	0.413***	0.499***	0.499***	0.803***
	(0.011)	(0.012)	(0.012)	(0.006)	(0.020)	(0.022)	(0.022)	(0.012)	(0.145)	(0.161)	(0.161)	(0.102)
Background Risk(Proxied by r_{it}^{obs})		-0.004*	-0.004*	0.005***		-0.008**	-0.008**	0.006***		-0.058**	-0.058**	0.023
		(0.002)	(0.002)	(0.001)		(0.003)	(0.003)	(0.002)		(0.026)	(0.026)	(0.016)
Other insurance			-0.001				0.030				0.008	
			(0.046)				(0.073)				(0.556)	
Observations	42457	38785	38785	38785	42457	38785	38785	38785	42457	38785	38785	38785
Outcome mean	0.222	0.240	0.240	0.240	0.310	0.337	0.337	0.337	2.568	2.805	2.805	2.805
Panel effect	Fixed	Fixed	Fixed	Random	Fixed	Fixed	Fixed	Random	Fixed	Fixed	Fixed	Random

The outcome variables are arisan participation in the previous year (Extensive margin) (Cols. 1 to 4), number of arisans participated by the individual (Intensive Margin) (Cols. 5 to 8) and log of arisans contributions in a year (Cols. 9 to 12). Sample includes adult individuals of age$\geq$15 years who are present in IFLS 4 & 5 survey rounds (when risk preferences were surveyed). All columns employ individual fixed effects except columns 4,8, and 12 which report individual random effects results. Observed risk aversion is an ascending scale; the higher its numerical value, the more risk averse a person. Covariates in all columns (not shown) include individual's age, education level, religion, household composition (proportion of children, adults & senior citizens), household's position in the per capita consumption quantiles; number of hospitals & health centers in the community and time fixed effects. In addition, for columns 9 to 12 (monetary contributions), inflationary trends in districts over time are controlled by (District $\times$ Time effects).
Standard errors in parentheses are clustered at individual level. (* p<0.10, ** p<0.05, *** p<0.01)

Table 3: Impact of social health insurance on background risk

	Risk Aversion Rank		Medium or Least Risk Averse Category (Rank 0,1)	
	(1)	(2)	(3)	(4)
Askeskin Insurance	-0.081**	-0.073**	0.031***	0.028***
	(0.037)	(0.037)	(0.010)	(0.010)
HealthShock	-0.079	-0.080	-0.024	-0.025
	(0.142)	(0.142)	(0.036)	(0.036)
Other insurance		-0.285*		0.085*
		(0.151)		(0.046)
Observations	38873	38873	43593	43593
Outcome mean	2.593	2.593	0.241	0.241
Panel effect	Fixed	Fixed	Fixed	Fixed
Std. Error	Cluster Ind	Cluster Ind	Cluster Ind	Cluster Ind

The outcome is background risk proxied by observed risk aversion (r_{it}^{obs}) in columns 1 and 2. Columns 3 & 4 have an indicator categorizing the two lowest risk aversion categories (r_{it}^{obs}=0,1) as outcome. r_{it}^{obs} is an ascending scale; higher its numerical value, the more risk averse a person. Standard errors are clustered at individual level.
(* p<0.10, ** p<0.05, *** p<0.01)

Table 4: Coefficient Stability - Bias adjusted Beta Results

	Model with Fixed effects	Model with No fixed effects
Arisan Participation (Extensive Margin)		
Beta - Uncontrolled model ($\mathring{\beta}$)	0.018**	0.036***
(Std. Err) [$\mathring{R}$]	(0.008) [0.028]	(0.006) [0.001]
Beta - Partial Control model ($\widetilde{\beta}$)	0.018**	0.018**
(Std. Err) [$\widetilde{R}$]	(0.008) [0.042]	(0.008) [0.799]
$R_{\max} = \text{Min}\{1.3 \times \widetilde{R}, 1\}$	0.055	1
Bias adjusted beta (β^{*})	0.017	0.013
Arisan Participation (Intensive Margin)		
Beta - Uncontrolled model ($\mathring{\beta}$)	0.039***	0.057***
(Std. Err) [$\mathring{R}$]	(0.012) [0.026]	(0.009) [0.001]
Beta - Partial Control model ($\widetilde{\beta}$)	0.038***	0.038***
(Std. Err) [$\widetilde{R}$]	(0.012) [0.051]	(0.012) [0.803]
$R_{\max} = \text{Min}\{1.3 \times \widetilde{R}, 1\}$	0.07	1
Bias adjusted beta (β^{*})	0.037	0.033
Arisan Participation (Log Rupiah Contribution)		
Beta - Uncontrolled model ($\mathring{\beta}$)	0.190**	0.337***
(Std. Err) [$\mathring{R}$]	(0.093) [0.031]	(0.064) [0.001]
Beta - Partial Control model ($\widetilde{\beta}$)	0.195**	0.195**
(Std. Err) [$\widetilde{R}$]	(0.094) [0.081]	(0.094) [0.803]
$R_{\max} = \text{Min}\{1.3 \times \widetilde{R}, 1\}$	0.106	1
Bias adjusted beta (β^{*})	0.198	0.161

Estimates of the model with no controls in Column 1 estimates are from the individual-level panel fixed effects model listed in equation (17). Within R-squared is reported in the square bracket.
Uncontrolled model in Column 2 are from a Pooled OLS model (without fixed effects) and overall R-squared is listed in square brackets.
The controlled models in both columns have individual-level and time dummies.
Standard errors of coefficients are in parentheses. The R-squared value of each regression is shown in square brackets. Estimates are obtained by using `pscalc` command in Stata. (* p<0.10, ** p<0.05, *** p<0.01)

Table 5: Treatment Effects IPWRA Results

	Arisan Participation (Extensive)		Number of Arisan (Intensive)		Arisan (Log Rupiah)		Background Risk
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Askeskin Insurance	0.049***	0.038**	0.083***	0.069**	0.712***	0.579***	- 0.092*
	(0.017)	(0.017)	(0.029)	(0.029)	(0.207)	(0.214)	(0.056)
Background Risk	No	Yes	No	Yes	No	Yes	-
Observations	42457	38785	42457	38785	42457	38785	38873

All models report the Average Treament Effect (ATE) coefficients, along with standard errors clustered at individual level. Sample includes adult individuals of age$\geq$15 years who are present in IFLS 4 & 5 survey rounds (when risk preferences were surveyed). Covariates in all columns for both output and treatment model include health shock, log total consumption expenditure, individual's age, education level, religion, household composition (proportion of children, adults & senior citizens), household's position in the per capita consumption quantiles, number of hospitals & health centers in the community and time fixed effects. All models also employ individual fixed effects using the Mundlak version of the fixed effects. In addition, for columns 5 and 6 (monetary contributions), inflationary trends in districts over time are controlled by (District $\times$ Time effects).
(* $p<0.10$, ** $p<0.05$, *** $p<0.01$)