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Experimental Identification of Asymmetric Information: Evidence on Crop Insurance in the Philippines

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Abstract

Asymmetric information imposes costs on a wide range of markets and may explain why some important markets, such as most agricultural insurance markets, have failed to develop. It is hard to empirically identify the different dimensions of asymmetric information but doing so is crucial for improving efficiency and solving market failures. I develop a new experimental methodology and apply it to study asymmetric information in crop insurance in the Philippines. Using a combination of preference elicitation, a two-level randomized allocation of insurance and detailed data collection, I test for and find evidence of adverse selection, moral hazard and their interaction – that is, selection on anticipated moral hazard behavior. I conclude that information asymmetry problems are substantial in this context and that they are unlikely to be reduced appreciably through contract redesign alone.

JEL: O1; D82; G22; C9

Keywords: insurance, adverse selection, moral hazard, selection on moral hazard, information asymmetries, selective trials, crop insurance, experiment, Philippines, agriculture

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1 Introduction

Small-scale farmers in developing countries are exposed to great financial risks from weather variations, pests and crop diseases that can be only partly addressed through informal risk sharing arrangements resulting in depressed investment and important short and long term negative welfare consequences for households(Maccini and Yang, 2009; Currie and Vogl, 2013; Rose, 1999). Formal insurance programs to address this risk fall primarily into two categories: traditional insurance that indemnifies based on farm-specific realizations and index-based insurance products that pay out based on an index such as the local rainfall or the average regional yield. Neither approach has evolved into well-functioning private markets for insuring major crops. In the traditional approach, payouts are highly correlated with farm-specific losses but verification of losses is costly and a high potential exists for adverse selection and moral hazard. Large-scale programs, such as the Federal Crop Insurance Program in the United States, rely on substantial government subsidies. The index-based approach is free of adverse selection and moral hazard but basis risk – the risk that insured farmers are not compensated for losses because those losses were not reflected in the index – is a major challenge. Index insurance typically has a positive impact on agricultural production by allowing households to increase investment and shift production to riskier but higher return crops (Karlan et al., 2014; Cole, Giné and Vickery, 2013; Cai et al., 2015; Cai, 2016; Carter et al., 2014). Despite these positive effects, demand has generally been low (Gine and Yang, 2009; Cole et al., 2013; Cole, Stein and Tobacman, 2014; Carter et al., 2014).[1] Low demand may be explained by risk averse consumers being driven away by basis risk (Clarke, 2016) or by lack of trust or understanding among farmers (Cole et al., 2013). Index insurance with substantial basis risk may also simply fall into a marketing "dead zone." Because the premiums for small-scale farms are low, financially sustainable sales and marketing would require high purchase and repurchase rates, as well as positive word-of-mouth (Cole, Stein and Tobacman, 2014), but high basis risk hinders all of these channels. For these or other reasons, index insurance for small-scale farmers is not currently a financially sustainable product with substantial market demand (Carter et al., 2014).

Given the current status, what are the ways forward in developing insurance for small-scale farmers? Future progress could occur through technological innovation, such as drones, satellite data or other new measurement strategies that reduce basis risk in index insurance or improve loss verification and pricing models in traditional insurance. Another avenue could be innovative contracts that meld index insurance with some degree of loss verification (Carter et al., 2014). To make progress in developing financially sustainable insurance for

[1] The index insurance studied by Karlan et al. (2014) is an exception in that demand was high.

small-scale farmers, absent technological innovations that substantially solve the preceding problems, it is critical to understand the degree and type of asymmetric information in traditional crop insurance. This understanding can be leveraged to improve traditional crop insurance and develop novel products that strike a new balance between basis risk and problems with asymmetric information.

In this paper I contribute to this understanding by studying information asymmetries in a traditional crop insurance contract in the Philippines using a series of randomized field experiments. In the Philippines a government-owned insurance company offers crop insurance for rice crops. This insurance covers crop losses due to specific natural hazards (such as typhoons, pests, and crop diseases). Payments are based on an ex post damage assessment by an agent of the insurance company. Since the insurance pays out based on the harvest losses from each particular plot, it is reasonable to expect substantial asymmetric information. I show that both adverse selection and moral hazard are substantial in this context and that the adverse selection is based both on selection on the inherent riskiness of plots and on the farmers anticipated moral hazard response to insurance. This is rare evidence of such information problems in a developing-country financial services market and among the first papers to identify selection on moral hazard. In this context, an important precursor paper, Karlan and Zinman (2009) found evidence of moral hazard but only weak evidence of adverse selection in a consumer credit market in South Africa. Similarly, Giné, Goldberg and Yang (2012) also found evidence of asymmetric information problems in an agricultural input loan market in Malawi (although they can not clearly separate moral hazard and adverse selection, the effect appears driven by moral hazard).

The design of the experiment was influenced by key challenges inherent in insurance (particularly issues of trust and insurance demand as discussed in Section 3) and opportunities presented by the local context, in particular the fact that farmers in this area routinely farm multiple plots. The experiment was conducted in two stages. In the first stage, I elicited farmers' preference ranking for insurance on plots in their portfolio by asking them to rank the top three plots for which they would prefer to have insurance. The farmers were told their first-choice plot would have a higher chance of receiving free insurance in a lottery. In the second stage, I randomly chose farmers to receive free insurance for a subset of their plots. I randomly selected which plots received insurance, but allowed their first-choice plots to have a higher chance of being covered. This approach generated across- and within-farmer variation in which plots were insured and provided an incentive for truth-telling (about the first-choice plot) in the first stage. Finally, I combined the data generated through this process with geospatial data on plot locations and environmental characteristics, administrative data from the insurance company and comprehensive survey data.

In Section 4, I model the joint determination of the plot choice decision and the farmers' allocation of preventative effort across plots. I allow for heterogeneity in both the inherent riskiness of plots and in the plot-specific cost of effort. Farmers select plots, taking into account their endogenous effort response to both plot characteristics and insurance. If the cost of effort is prohibitively large on all plots, then farmers select plots that are large and have high inherent riskiness. If the cost of effort is lower, allowing for a sizable effort response by the farmer, then a tradeoff exists between choosing plots that have high expected damages and those on which a relatively large effort cost can be saved if insured. The model therefore implies that, in addition to classic moral hazard, two types of adverse selection may be present. First, selection on "baseline risk"; that is, selection on the expected damages on a plot, taking into account the endogenous effort response to plot characteristics but not the endogenous response to insurance. And second, "selection on moral hazard"; that is, selection on the plot-specific anticipated effort response to insurance.

The paper contains three empirical sections (Sections 6 - 8). In the first, I separately estimate adverse selection in plot choice and classic moral hazard. I estimate moral hazard by comparing the damage experience on randomly insured and uninsured plots of the same farmer and estimate adverse selection by comparing damages on the farmer's first-choice plot to damages on other plots of the same farmer. I find strong evidence for moral hazard and adverse selection. Farmers select plots that are prone to flooding and crop diseases and this selection leads to about 20% higher damages on first choice plots compared with the farmers' other plots. To investigate moral hazard, I separate the harvest losses into two components: loss due to typhoons and floods, and loss due to pests and crop diseases. This distinction is motivated by expectations at the start of the project that pests and crop diseases are more preventable than typhoons and floods.[2] I find evidence for moral hazard in the prevention of pests and crop diseases. Harvest loss due to these causes is about 22% higher on randomly insured plots compared to uninsured plots. In contrast, I find no evidence of moral hazard in the prevention of typhoon and flood damage.

In the second, I investigate the effect of insurance on investment (as measured by fertilizer expenditures) and use the across-farm randomization to investigate whether insurance on one plot has implications for farming decisions on other plots. I find evidence that farmers use less fertilizer on insured plots, although this effect is small (3-5%). This finding is consistent with moral hazard because under moral hazard insured plots are higher risk than uninsured plots. This finding provides further confidence that the observed moral hazard effect is indeed

[2] The insurance company makes the same distinction and offers an insurance package that covers only typhoons and floods as well as a comprehensive package (used in this study) that also includes coverage for pests and crop diseases.

identifying moral hazard. It also implies that subsidies for this type of insurance may reduce aggregate investment but any such effect would be small. I do not find any evidence that insurance on one plot alters investment on the farmers' other plots. The possible mechanisms for such an effect, such as scale economies (such as in fixed costs of obtaining inputs), wealth effects (from the reduced investment on insured plots) or important background risk effects (that is, incentives for greater investment on uninsured plots through reduced background risk from insured plots), appear to either be small or cancel each other out.

In the third, I develop an empirical strategy to disentangle selection on what I have termed "baseline risk" from "selection on moral hazard." The strategy uses plot characteristics collected at baseline, which predict about 30% of the observed adverse selection effect, to construct measures of predicted damages separately for randomly insured and uninsured plots. I then study whether selection is based on the predicted values for uninsured plots (i.e., baseline risk) or on the difference (i.e., selection on moral hazard). The difference is computed by subtracting predicted values on control plots from predicted values on insured plots and it represents the predicted moral hazard based on baseline characteristics. I find that farmers appear to select on both of these dimensions.

This paper primarily contributes to the literature on agricultural insurance for small-scale farmers in developing countries by complementing the recent literature on index insurance[3] and supplementing the existing literature on crop insurance (see L Hueth and Hartley Furtan (1994); Miranda and Glauber (1997); Just, Calvin and Quiggin (1999) and Makki and Somwaru (2001)). In designing an insurance product an insurer must choose its devil by trading off high basis risk against problems with asymmetric information. To design effective policies, it is essential to understand the implications of this tradeoff. I contribute to this understanding in two ways. The key contribution is to identify and quantify the separate dimensions of asymmetric information in a crop insurance product in the Philippines. This evidence can be used to improve traditional crop insurance products and to develop new products that minimize both basis risk and problems with asymmetric information. A second contribution is that I study how this type of insurance affects investment. In contrast to the index insurance literature, I do not find increased investment; in fact the evidence supports a small decrease in fertilizer use. I interpret this outcome as being due to the moral hazard inherent in the insurance for pests and crop diseases. Removing this coverage and focusing only on weather related risk may result in an insurance that provides incentives for

[3]See Gine and Yang (2009); Cole, Giné and Vickery (2013); Karlan et al. (2014); Mobarak and Rosenzweig (2013, 2012); Cole et al. (2013); Cole, Stein and Tobacman (2014); Cai et al. (2015); Cai, de Janvry and Sadoulet (2015); Dercon et al. (2014); Hill, Robles and Ceballos (2016); Cai (2016) and citations within Carter et al. (2014), who provide a recent review of this literature.

investment.[4]

The paper also makes several contributions to the more general literature on asymmetric information, both in the context of developing countries and more generally. First, because farmers in this study control multiple insurable units (plots) I am able to study their relative demand for insurance based on their understanding of the relative risk of loss across their plots. This approach allows a certain separation between risk on the one hand and the farmers' individual preferences and constraints on the other. This separation is important because adverse selection based on heterogeneity in risk can be offset by advantageous selection (de Meza and Webb, 2001) induced by interactions between risk and risk preferences.[5] Second, I study the issue of *selection on moral hazard*, where consumers demand insurance based in part on their anticipated moral hazard response, which has been done in only one existing paper (Einav et al., 2013). This effect can be identified directly from the experiment but with low statistical power and I rely on an alternative test that takes advantage of baseline data.

Finally, the paper contributes to a recent literature on enhancing the information produced by randomized experiments. The design in this paper can be generalized as a two-step procedure in which incentivized choices are obtained in the first step and treatment is allocated according to preferences in the second step. This procedure is related to the one developed in Chassang, Padró i Miquel and Snowberg (2012), but it focuses on the choice between two alternative treatments rather than on the willingness-to-pay for a single treatment or program.

The paper proceeds as follows. I first provide background on the economic environment and previous literature on asymmetric information in Section 2. Next, I describe the design of the experiment in Section 3. I then present the model and derive empirical implications in Section 4. In Section 5, I discuss the implementation, describe the data and examine the integrity of the experiments. Next, I present the three empirical sections. In Section 6 I separately estimate adverse selection and moral hazard; in Section 7 I investigate resource allocation over the farmers' portfolio of plots and mechanisms of moral hazard; and in Section 8, I disentangle selection on baseline risk from selection on moral hazard. Finally, I conclude

[4]Since this type of insurance is tied to a particular type of crop and a particular tract of land, incentives would only be provided for intensifying production (such as through fertilizer use) as opposed to the type of investment response often associated with weather-index insurance, which is typically based on extending production to a larger area and shifting to higher risk but higher return crops (Karlan et al., 2014; Cole, Giné and Vickery, 2013; Cai et al., 2015; Cai, 2016; Carter et al., 2014).

[5]A sizable body of literature confirms the possibility of advantageous selection with results largely diverging by insurance type. Health insurance and annuity markets tend to show adverse selection while the evidence points to advantageous selection in life and long-term care insurance. See Cutler, Finkelstein and McGarry (2008) and references within, e.g., Cawley and Philipson (1999); Finkelstein and Poterba (2004); Finkelstein and McGarry (2006); and Fang, Keane and Silverman (2008).

in Section 9.

2 Background

2.1 Economic Environment

Rice is the staple crop in the Philippines, and the major crop in the study area's region. All farmers participating in this study are growing rice within the Tigman Hinagyaan Inarihan Regional Irrigation System north of Naga City in the Bicol region. The study area is located on low-lying plains and is characterized by a high density of contiguous, usually irrigated rice plots. The yield per hectare is typical for the Philippines. Production in this area is at risk because of floods, droughts, pests, crop diseases and, most importantly, typhoons (tropical cyclones) that hit the Philippines at a rate of about 15 per year.

Farmers in the area use a variety of income and consumption smoothing strategies to manage production risk. As in other contexts, it is very common to till multiple parcels and to engage in other income generating activities, such as driving tricycles, operating shops or having family members work in a nearby town or city as income-smoothing strategies(Rosenzweig and Binswanger, 1993; Dercon, 1996; Morduch, 1995). In a different region of the Philippines, Fafchamps and Lund (2003) document a substantial role of gifts and informal loans as a way to smooth consumption. Extensive literature describes how such income and consumption smoothing strategies are employed elsewhere.[6] However, these strategies typically do not allow households to fully smooth their consumption[7] and they can be unreliable, offering little or no protection when communities experience large shocks such as widespread drought (Kazianga and Udry, 2006; Porter, 2012).

To address this uninsured risk the Government of the Philippines established the Philippines Crop Insurance Corporation (PCIC). Among its products is multi-peril crop insurance for rice farmers. PCIC is fully owned by the government and the insurance is generally offered to farmers with a premium subsidy of about 55% but during this experiment the participating farmers got the insurance for free through an additional 45% subsidy paid by research funds. The insurance contract offered by PCIC covers rice production on a particular field and pays out in the event of damages to that specific field from one of the covered causes. These causes include typhoons, floods, droughts, various pests (rats and insects) and

[6]See Morduch (1995); Rosenzweig and Binswanger (1993); Dercon (1996); Kochar (1999, 1995); Deaton (1992); Udry (1994).

[7]Townsend (1994); Attanasio and Davis (1996); Fafchamps and Lund (2003); Rosenzweig and Binswanger (1993); Rose (1999); Maccini and Yang (2009)

crop diseases (especially tungro, which is spread by insects).[8] Any particular damage event must cause at least 10% loss of harvest to be eligible for a claim. If a damage event causes more than 10% damage, an insured farmer files a notice of loss to the company, which sends an insurance adjuster to verify damages. The contracts have a maximum per-hectare payout (in this study, 20,000 pesos or about $430) and they pay out based on the share of harvest lost and the timing of loss (farmers can often plant again if damages occur early in the season). In addition, if losses from pests and crop diseases are localized and not due to a wider outbreak affecting many farmers (as determined by the local government agricultural office), then the payouts are capped at 30% of the policy value. A copy of PCIC's informational flier for the rice crop insurance is included in the Online Appendix.

The fact that payouts are based on the percent of harvest lost rather than an evaluation of the absolute loss is important. It means that payouts are unrelated to underlying productivity or marginal investment (such as fertilizer). A total loss on a relatively unproductive plot that was minimally fertilized would bring the same payment as a fully fertilized and productive plot provided they are the same size and both had full standing crops of rice before the damage. This approach makes verification easier because the adjuster only has to assess the share of crops that are damaged rather than the value of counterfactual harvest. But, as I discuss later, it has potential adverse effects on investment and demand for insurance.

Even with the government premium subsidy, demand for this insurance is limited (Reyes and Domingo, 2009). In the 2000's about 30,000 rice and corn farmers were covered each year. In early 1990's, when premium subsidies were even higher, these programs covered over 300,000 farmers. In the next section I describe the experiments that I designed and implemented to understand the degree to which asymmetric information increases the costs of providing this insurance, leading to lower demand and necessitating public subsidies.

2.2 Identification of Asymmetric Information

An extensive literature analyzes the reasons for the absence or underperformance of financial markets in developing countries (see e.g., Hoff and Stiglitz (1990); Besley (1994); Conning and Udry (2007)). In particular, the seminal contributions of Stiglitz and Weiss (1981) and Rothschild and Stiglitz (1976) show how adverse selection can cause market failures in credit and insurance markets. In the case of crop insurance, previous research (mostly based on markets in the United States and Canada) has identified adverse selection, moral hazard,

[8] The insurance also covers rare events such as volcanic eruptions and earthquakes but it excludes some minor pests such as birds and snails. We ignore damages from birds and snails in the analysis. The amount of damages from birds is trivial. Losses from snails are nontrivial, but they are small and primarily occur when plants are seedlings (before transplanting), so it is impossible to assign per-plot damage rates.

and spatial co-variability of risk as the main reasons for the failure of private markets and public schemes (L Hueth and Hartley Furtan, 1994; Miranda and Glauber, 1997; Just, Calvin and Quiggin, 1999; Makki and Somwaru, 2001).

Empirical identification of information asymmetries is difficult using data normally available to insurance companies and researchers. It is particularly challenging to separately identify the role of each dimension of this asymmetric information, such as that based on heterogeneity in individual preferences, inherent risk, or cost of effort. First, it is very challenging to identify moral hazard without some exogenous shift in coverage. Second, since both preferences and risk type are (at least partly) unobserved, it is hard to identify the degree to which selection is based on private information on risk type versus private information on preferences. This difference has crucial implications for the insurance provider and for market development. Selection on risk type leads to higher payouts and can cause the market to break down (Rothschild and Stiglitz, 1976), while selection on preferences is less likely to be a cause for higher payouts. In fact, in many markets (such as automobile insurance and life insurance), selection on risk preferences is likely to offset selection on risk type (de Meza and Webb, 2001; Cutler, Finkelstein and McGarry, 2008). Third, identifying selection on private information that influences the degree of ex post moral hazard is very difficult; Einav et al. (2013) term this mechanism "selection on moral hazard." This mechanism would be operating in our context if a farmer chooses to buy insurance on a plot that is, for example, close to residential areas (hence susceptible to rats), next to a plot of a neighbor with lax pest management practices (hence susceptible to insects and other pests), or far from her home (high fixed cost of monitoring), explicitly because, once the plot is insured, she can save a substantial amount of effort in preventing damages.

A positive correlation between choice of insurance coverage and accident occurrence conditional on data that an insurance provider can observe has been shown to be a robust test of the presence of information asymmetries, but it cannot distinguish between different dimensions of asymmetric information (Chiappori and Salanie, 2000; Chiappori et al., 2006). Recent contributions have used dynamic data, difference-in-difference techniques, direct data on subjective beliefs, and structural estimation in attempts to better identify specific components of asymmetric information (Abbring et al., 2003; Finkelstein, McGarry and Sufi, 2005; Cardon and Hendel, 2001; Cohen and Einav, 2005; Einav et al., 2013; Finkelstein and McGarry, 2006).

A potential solution to these challenges (and the one employed here) is to use experimental methods. The Rand Health Insurance Experiment pioneered work in this area by identifying moral hazard (but not adverse selection) in health insurance by randomly allocating families to different coverage levels.[9] To study adverse selection and moral hazard together requires a multi-step experimental design, which has not been implemented previously for an insurance market. Karlan and Zinman (2009) used a two step design to identify both of these dimensions in a consumer credit market in South Africa by randomizing interest rate offers and then surprising some consumers with a better contract interest rate. It would be appealing to build on this experimental design to study insurance by randomizing the premium offered to consumers and then in a second step implement an exogenous shift in coverage by increasing policy value, reducing deductibles or providing free insurance.[10] Several features of agricultural insurance in developing countries make this approach challenging in our context. First, insurance and credit are diametrically opposite in terms of the trust required to sustain a market. An insurance company must gain the trust of a consumer while it is the bank that must decide on the trustworthiness of the consumer seeking credit. As a result, take-up is likely to be low as it tends to be for crop (or index) insurance products in developing countries, which would necessitate extending offers to a very large universe of farmers. In addition, it may be necessary to build trust through repeated engagement with a population, which would complicated designs based on the element of surprise. Second, with a large initial universe of participants, engagement becomes logistically challenging. In particular, implementing agricultural surveys among a large sample of farmers over a vast geographic area is very expensive.

3 Experimental Design

In light of these challenges I designed the experiments with the goal of maximizing the information that they would provide about asymmetric information in this insurance market and the behavior of farmers when engaging with a crop insurance contract of this type without requiring that the farmers purchase insurance with their own funds. To disentangle many of the relevant information asymmetries, I incorporate three key features in the experimental design: (1) I take advantage of the fact that farmers in this context routinely till multiple plots of land, and designed the experiment and data collection to consider the plot as the base unit of analysis, (2) I introduce experimental variation across plots within the same farm and obtain incentivized choices at the plot level and (3) I introduce experimental variation in insurance coverage across farms.

The study design for each season was as follows:

[9] Key references include Manning et al. (1987) and Newhouse and Rand Corporation. Insurance Experiments group (eds.) (1993).

[10] In fact, early designs of these experiments were based on this approach.

Step 1: Each farmer was asked to rank the top three plots within their portfolio of plots that they would prefer to have insured. The farmers were told that their top choice plot would have a higher chance of receiving free insurance in the lottery.

Step 2: Baseline survey (if not completed in earlier seasons).

Step 3: Farmers were entered into a lottery and randomly allocated to three groups:

Group A (66.5%; Full Randomization): Received insurance on a random half of plots.

Group B (3.5%; Choice): Received insurance on first-choice plot and a random half of remaining plots.

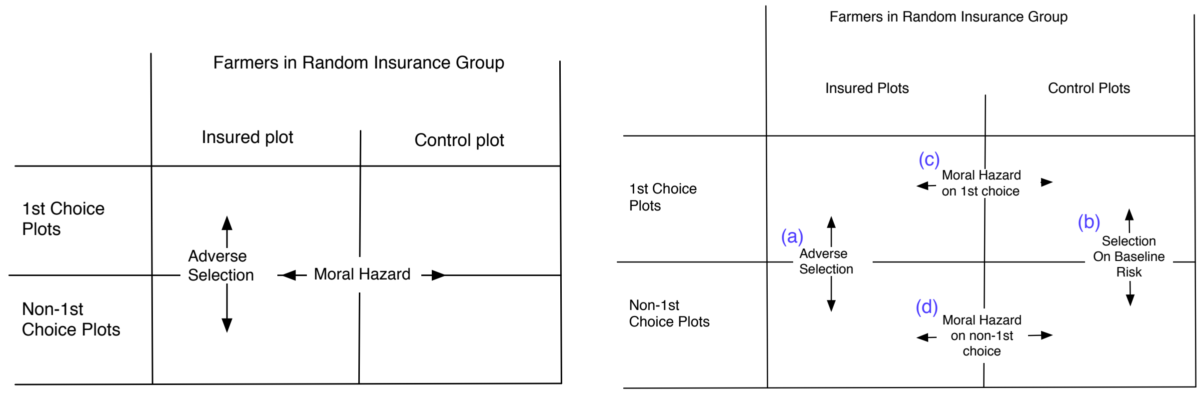
Group C (30%: Control): Received no insurance.

Step 4: Two follow-up surveys were conducted, one after planting and another after harvest.

The farmers were not informed of the exact randomization probabilities, but they were told that their first-choice plot would have a higher chance of receiving insurance coverage. This (Group B) is a truth-telling mechanism. It ensures that it is incentive compatible for farmers to reveal their true preference for their first-choice plot. The farmer-level randomization was stratified by geographic location.[11] Insurance was allocated to plots in Group A using block randomization within the farm such that half of the farmers' plots were insured. Farmers with an odd number of plots, n, were randomly selected to receive insurance on $\frac{n-1}{2}$ or $\frac{n+1}{2}$ plots. After insurance had been allocated to the first-choice plots of farmers in Group B, their remaining plots were randomly allocated insurance using the same procedure as in Group A.

Figure 1a depicts the basic identification strategy used to separately identify adverse selection and moral hazard. To identify adverse selection, I compare the farmer's first-choice plot to her other plots, excluding first-choice plots of farmers in the Choice Group. Since insurance coverage is random in this sample of plots, this provides a test for adverse selection. I will test this both by comparing measures of predicted damages, actual damages and payouts. To identify moral hazard, I compare randomly insured and uninsured plots within and across farmers. In principle, the design allows me to identify moral hazard separately for first-choice plots and for other plots and therefore identify whether the farmer selects a plot based in part on anticipated moral hazard behavior. Figure 1b depicts how this test would

[11] In the first season, the experiments were conducted in a relatively small geographic area and we stratified by the number of plots instead.



(a) Identification of adverse selection and moral hazard

(b) Identification of selection on baseline risk

Figure 1: This figure shows the basic identification strategies

be carried out (here I also exclude first-choice plots of the Choice Group so insurance choice and insurance status are orthogonal). Comparing first-choice plots and other plots in the subsample that were not allocated insurance (comparison (b) in Figure 1b) identifies what I term *selection on baseline risk*, that is, selection on risk characteristics of plots that do not interact with moral hazard. A similar comparison among insured plots (comparison (a) in Figure 1b) identifies the full degree of adverse selection, including the former effect and any interactions with moral hazard. This interaction exists if farmers choose plots based in part on their anticipated moral hazard behavior. In terms of the effects depicted in Figure 1b, we have effect (a) = effect (b) + (effect (c) - effect(d)). I do not have enough statistical power in practice to carry out this test directly but I develop and conduct a modified test of the *selection on moral hazard* effect in Section 8.

4 A Model of Preventative Effort and Choice of Plot for Insurance

4.1 Setup and Maximization Problem

In this section I develop a model of the decision problem that the farmers face in the experiments. In the model, farmers face the possibility that they may lose part of each plot's harvest to a natural hazard. Farmers make two decisions. First, they select one plot to designate as their "first choice." Next, they allocate preventative effort for reducing crop loss from natural hazards to each of their plots. The major feature of the experiment's design is that the insurance choice is only probabilistic. The plot chosen may or may not receive insurance and the insurance is randomly allocated to plots. Given this feature of the data, I model insurance choice and effort as a joint decision for the purpose of studying insurance choice. I then consider the insurance to be exogenously determined to study moral hazard, and extend the model to consider the farmer's effort and variable investment decisions.

Consider a farmer with a portfolio of plots, $\Omega = ((A_1, \theta_1), ..., (A_N, \theta_N))$, indexed by j. Each plot, j, is of size A_j hectares, has risk characteristics θ_j, and is assumed to produce a maximum output of 1 per hectare (I relax this last assumption in Section A.4). Some of this output may be lost to natural hazards. The share of harvest lost, S_j, is a random variable that I assume is uniformly distributed on $[0, \theta_j(1 - e_j)]$ where $\theta_j \in (0, 1]$ indexes the risk characteristics of the plot and $e_j \in [0, 1]$ is the effort expended to reduce damages. Let $\theta = (\theta_j)_{j=1}^N$ be the vector of plot risk characteristics and $\mathbf{e} = (e_j)_{j=1}^N$ the vector of effort levels across plots. I assume that the insurance provider does not observe plot characteristics and effort levels.[12] I also assume that, conditional on θ and $\mathbf{e}$ (which determine the support of the distribution of losses), the harvest losses are independent random draws across plots.[13] This implies that effort and investment decisions on plot j of farmer i are independent of whether plot j' of the same farmer is insured.

When a plot is insured the farmer receives a payout of LS_j per hectare, where $L < 1$ is the per hectare insurance coverage.[14] I denote the indicator for insurance coverage with $\alpha_j \in \{0, 1\}$ and define $\alpha = (\alpha_j)_{j=1}^N$. This is now a choice variable, with the restriction that $\sum_{j=1}^N \alpha_j = 1$, representing the choice that the farmer faces in choosing one plot as their first choice (later on I replace α with $\alpha^{assigned}$ to represent the exogenously assigned insurance allocation).[15]

[12] This assumption is consistent with the context: per-hectare prices only depend on the season and the geographic area; furthermore, no monitoring of farm practices (such as pesticide or insecticide use) takes place. The study area is fully contained in one pricing area, so all farmers face the same per-hectare prices. Since all insurance is free in the experiment, the tradeoff that the farmer faces in selecting a plot for insurance is the opportunity cost of not insuring a different plot.

[13] This assumption provides tractability, but of course shocks are not uncorrelated across plots. Rather, they are typically positively correlated, particularly for aggregate shocks such as typhoons. If farmers take into account the likely positive correlation between shocks then they are likely to shift in some cases to choosing the largest plot rather than the plot with the highest expected damages to maximize their payment if, for instance, they experience total loss on all plots. This would lead to some downward bias in the adverse selection estimates reported later. In the empirical section, this issue is also addressed through the design of the experiment (the plot randomization) and through data collection (especially the collection of spatial coordinates of plots, allowing spatially corrected standard errors). Even if shocks are independent across plots, the farmers' input decisions on plot j are not independent of whether plot j' is insured for general utility functions. The design of the experiment, in particular the two-stage randomization procedure, allows testing these implications of the model – that is, whether reducing production risk on plot j has implications for production decisions on plot j'.

[14] I define $L < 1$ for simplicity, but this can be thought of as the maximum payout divided by the typical harvest if no damages occur. The average harvest is valued at 47.3 thousand pesos, the value of the average damages are 15.5 thousand pesos, and the maximum payout in the experiments is 20 thousand pesos. These numbers yield an $L = \frac{20}{15.5+14.7} = 0.32$.

[15] The farmer's choice is only probabilistic but I assume that the farmer chooses a plot in the same way as she would do if insurance was to be assigned with probability 1.

The total farm profits are stochastic and given by $\Pi(\alpha, \mathbf{e}) = \sum_j \{A_j((1-S_j) + \alpha_j LS_j)\} - C(\mathbf{e})$ where C is the cost-of-effort function. Given their stochastic nature, the resulting utility derived by the farmer is based on her risk aversion and the degree of other risk-sharing arrangements that are in place. I assume the farmers' preferences can be represented by a mean-variance utility over total future profits: $E[U(\Pi)] = E[\Pi] - \rho(1-\tau)Var(\Pi)$. In this setup, the variability in profits cause a utility penalty (according to the farmer's risk aversion) but this penalty is tempered by the degree of informal risk sharing that the farmer is engaged in. A farmer whose risk-sharing network allows full informal risk sharing ($\tau = 1$) would only derive utility from the first term.

Aside from the farmer's portfolio of plots, I model two other factors that are likely to have first-order importance in the effort and insurance choice decisions of farmers. First, each farmer has a degree of risk aversion that I model with the parameter ρ. Second, given the well-documented role of informal risk sharing in a context such as this, I index the strength of each farmer's risk-sharing network with the parameter $\tau \in [0, 1]$. A farmer with $\tau = 1$ is fully insured informally and only cares about expected profits whereas the utility of a farmer with $\tau = 0$ is fully penalized (according to her risk aversion) for variability in farm profits. The farmers maximization problem is to choose one plot as the preferred plot for insurance and then choose effort level on each plot conditional on its insurance coverage to maximize expected utility:

$$\max_{\boldsymbol{\alpha},\mathbf{e}} E[\Pi] - \rho(1-\tau)Var(\Pi) \tag{1}$$

subject to $\sum_{j=1}^{N} \alpha_j = 1$, $\alpha_j \in \{0, 1\}$ and $e_j \in [0, 1]$. The core of the research design is that the experiment allows breaking this maximization problem into two parts, identifying the two choice variables separately – that is, identifying insurance choice based on inherent plot characteristics and anticipated effort allocation, and then separately (from selection) identifying effort and investment responses to insurance. In the next section I first analyze the optimal effort allocation as a function of insurance coverage. This serves as both an analysis of optimal behavior after the insurance allocation in the experiment is known and as input into the first-stage choice problem.

4.2 Optimal Effort

To derive the optimal effort, I assume that the per-hectare cost-of-effort function is separable and takes the form $c(e_j) = \psi_j e_j$ where ψ_j represents the plot-specific cost of effort. Here the ψ's may, for example, represent plot-specific features that hinder prevention of pests or insects, or they may represent the ease or difficulty of draining the plot after heavy rains. They may also incorporate other sources of the cost of effort, such as distance from home or scale economies (since they are per-hectare costs). In the case of distance from home, the ψ's are not characteristics of the plot per se, but from the perspective of the farmer, they can be treated as plot characteristics.[16] Total effort costs are assumed to be separable and additive: $C(\mathbf{e}) = \sum_{j=1}^{N} A_j \psi_j e_j$. Given this setup, the effort of farmer i on plot j is a function of the farmers' risk aversion (ρ, omitting the farmer subscript i) and plot-level attributes: the insurance coverage (α_j), the inherent riskiness of the plot (θ_j), the cost function parameter (ψ_j) and plot size (A_j). I show in Appendix A that optimal effort is given by:

$$\hat{e}_j(\alpha_j, \theta_j, \psi_j, A_j, \rho, \tau) = \begin{cases} 0 & \text{if } \psi_j \geq w_j + \frac{2}{3}\rho(1-\tau)A_j w_j^2 \\ 1 - \frac{3}{2}\frac{\psi_j - w_j}{\rho(1-\tau)A_j w_j^2} & \text{if } w_j < \psi_j < w_j + \frac{2}{3}\rho(1-\tau)A_j w_j^2 \\ 1 & \text{if } \psi_j \leq w_j \end{cases} \tag{2}$$

where $w_j = \frac{1}{2}(1-\alpha_j L)\theta_j$. Figure I.1 illustrates optimal effort as a function of the plot-specific cost of effort (ψ) for insured and uninsured plots. Effort is lower on insured plots in the range where (1) cost of effort is large enough that effort is less than 1 if the plot is insured but (2) small enough that effort is positive if the plot is uninsured – that is, if $\psi \in (w^1, \hat{w}^0))$ in Figure I.1. The model therefore implies moral hazard over this range.

In this section I have assumed that the α_j's are given. These findings therefore describe both (1) the maximization problem the farmer faces after learning of the insurance allocation in the experiment and (2) the problem that the farmer expects to face during the cropping season when taking the insurance choice decision. In the experiment, after the farmer is informed of the insurance allocation, the problem simplifies. Instead of the farmer's problem in Section 4.1 she now maximizes only over $\mathbf{e}$ (effort). Then, α (insurance) is no longer a choice variable but is replaced by $\alpha^{assigned}$, which is exogenous and is not limited to adding up to one over all plots. I discuss the empirical implications for analyzing moral hazard in Subsection 4.4. First, I use this characterization of optimal effort allocation to derive the optimal insurance choice.

4.3 Insurance Choice

To characterize the optimal insurance choice of farmers in the experiment, I consider and contrast two different levels of sophistication on the part of the farmer. First I consider the

[16] Scale economies can be due to different plot sizes or due to the same farmer having two plots close to each other. About 35% of the plots in the sample are adjacent to at least one other plot of the same farmer. Although the model considers only one type of damage, in reality farmers face multiple natural hazards, each associated with a different plot-specific cost of preventative effort. The primary distinction in the paper will be between cost of effort in preventing typhoons and floods versus pests and crop diseases. A priori, one might expect ψ to be very high for all plots in the case of typhoons and floods, but lower (and possibly variable across plots) for pests and crop diseases.

insurance choice of a farmer that is partially myopic in that the anticipated effort response to insurance is not taken into account, and the farmer instead chooses insurance with the assumption that the plot will be farmed in the same manner as would normally be done without insurance.[17] Based on the utility output of plot j (see Appendix A), the perceived utility gain from insurance on plot j for a farmer constrained by myopia of this type is

$$\begin{aligned}\Delta u_j^{\text{myopic}} &= u_j^{\text{myopic}}(1, \theta_j, \psi_j, A_j, \rho, \tau) - u_j^{\text{myopic}}(0, \theta_j, \psi_j, A_j, \rho, \tau) \\ &= \frac{1}{2} A_j \theta_j L (1 - \hat{e}_j^0) - \frac{\rho(1-\tau)}{12} A_j^2 \theta_j^2 ((1-L)^2 - 1)(1 - \hat{e}_j^0)^2 \end{aligned} \tag{3}$$

The first term is the expected payout on plot j if the farmer applies effort as she would without insurance. The second term is the expected gain in utility from the reduction in the variance of profits that the insurance provides (it contributes positively to utility since $(1-L)^2 - 1 < 0$). In this case, the only utility gain from insurance is the payout received and this payout is maximized by choosing the plot that has the highest expected damages – that is, the highest product of area and expected damages per hectare (a proof can be found in the Online Appendix).[18]

Now contrast this choice with the insurance choice of a more sophisticated farmer who anticipates her effort response to insurance and makes an optimal decision with this in mind. The perceived utility gain from insurance in this case is

$$\begin{aligned}\Delta u_j^{\text{sophisticated}} &= \frac{1}{2} A_j \theta_j \left[(1 - \hat{e}_j^0) - (1-L)(1 - \hat{e}_j^1) \right] \\ &+ \frac{\rho(1-\tau)}{12} A_j^2 \theta_j^2 \left[(1 - \hat{e}_j^0)^2 - (1-L)^2 (1 - \hat{e}_j^1)^2 \right] \\ &+ A_j \psi_j (\hat{e}_j^0 - \hat{e}_j^1) \end{aligned} \tag{4}$$

As before, the farmer derives utility gain from the increase in expected profits inclusive of insurance payouts (the first term above) and the decrease in the variance of profits (the second term) but in contrast to the myopic farmer she anticipates her moral hazard behavior when evaluating these terms. In contrast to the earlier case the farmer also takes into account the third term, which captures the utility gain from the effort that the farmer saves when the plot is insured. Therefore, in this case the farmer balances the gains from an insurance

[17] The farmer does, on the other hand, anticipate how the effort level is influenced by plot characteristics. For example, if a plot has a high risk of floods but this risk is easily prevented by low-cost effort, the farmer may prefer insurance on a plot that has a medium risk of damage but for which no low-cost preventative solution is available.

[18] Note that the expectations of damages are conditional on expected efforts, which are in turn based on all aspects of the model other than insurance status. In particular, the farmer anticipates any effect that plot characteristics may have on her effort.

payout against the gains from saved effort. This version implies that farmers may select not only on the inherent riskiness of plots but also on the ability to engage in moral hazard. This effect was termed *selection on moral hazard* by Einav et al. (2013), who identified it by using a structural model and data on health insurance in the United States.

4.4 Empirical Implications

The data allows me to test various features of the model. Some of these are not specific to this model (almost any model would for example predict adverse selection and moral hazard in this data) but they are listed here for completeness. The model predicts that farmers prefer insurance on plots that are large and risky, which results in adverse selection unless there is a strong negative correlation between plot size and risk of damage. Empirically this correlation seems to be small and positive (plot size and total damages have a correlation of about 0.05). Nevertheless, I condition on plot size in the specification later on to prevent a false-positive test of adverse selection. An important feature of the model is the possibility that farmers choose not only according to the risk profile of their plots, but they may also select on plot-specific heterogeneity in cost of effort, inducing a "selection on moral hazard" effect. In Section 8 I empirically investigate whether the data fit better with a model in which farmers select only on the risk profiles of plots (and their area) or whether they are more sophisticated, anticipating their effort response to insurance and choosing in part on this basis.

The model predicts that we will observe moral hazard behavior for hazards that can be prevented at a cost that falls within a specific range (see Figure I.1). Actions that carry a negligible or prohibitively large cost are unlikely to be affected by insurance status but many actions, such as using pesticides or insecticide, or removing infected plants, could fall within this range. In Section A.4 in the Appendix I extend the model to allow for a productive investment input (rather than assuming a fixed harvest when there are no damages) and show that farmers have an incentive to reduce the use of non-preventative productive investment (such as fertilizer) on insured plots. This highlights a negative implication of the insurance contract design, which does not insure marginal productive investment since payouts are based on the percentage of harvest lost (rather than absolute loss).[19] It also provides another test for moral hazard.

The mean-variance utility assumed in characterizing the optimal effort and the insurance choice decision implies that getting insurance on one plot does not influence a farmer's decisions on other plots. This assumption does not hold for general utility functions and

[19] This design feature is likely not there by mistake but rather due to the difficulty that insurance adjusters would face in evaluating expected yields, particularly for damage that occurs early in the cropping season.

it may not fit the data well, for example if the farmer puts more weight on preventing outcomes below a certain threshold. This approach could be the case if the farmer is close to subsistence level or if, as is common in the study area, the farmer takes out an informal production loan with high penalties for late payment. By removing some risk to income from an insured plot, the insurance coverage may allow a farmer to take more risk on an uninsured plot. [20] In Section 7, I test which of these different predictions fit the data better.

5 Sample, Experimental Integrity and a Description of the Data

Under my direction, Innovations for Poverty Action (IPA)[22] conducted the experiments and data collection from the spring of 2010 through mid-2012. IPA staff invited farmers in the study area who fulfilled certain eligibility criteria (described below) to participate. The implementation started in the 2010 wet season (June - September) with a small pilot experiment with 52 farmers, followed by full-scale experiments and data collection during the following three cropping seasons. The sample was gradually expanded, from 106 farmers with 291 plots in the dry season (December - April) of 2010-2011, to 285 farmers with 806 plots in the wet season of 2011 and 447 farmers with 1302 plots in the dry season of 2011-2012. After each round, farmers were invited to participate in subsequent rounds. Figure I.2 shows parcels that were part of the study in at least one of the seasons.

Rice is grown in this area by owner-operators or through a variety of informal contractual arrangements between tillers and owners. This context necessitated a clear definition of "farmer." We defined a person to be the farmer of an agricultural plot only if that person was both (1) the principal decision maker for farming decisions, and (2) the bearer of a majority of the production risk. Because of the design of the experiment (involving within-farm plot randomization) we focused only on farmers with two or more agricultural plots. We attempted to recruit as many farmers as possible in the sample area who satisfied the eligibly criteria of farming two eligible plots within the geographic area of the study. Plots in the study area were eligible if they were irrigated, traditionally rice-growing plots, and between

[20]This concept of *background risk* and the related concept of *risk vulnerability* have been studied extensively in the theoretical literature (Gollier and Pratt, 1996; Christian, 2006; Heaton and Lucas, 2000; Eeckhoudt, Gollier and Schlesinger, 1996) but the empirical evidence is more limited.[21] Cardak and Wilkins (2009) find that background risk due to volatile labor income or health status is important for the financial portfolio choice of Australian households. This concept has also been studied in laboratory experiments by Harrison, List and Towe (2007), Lee (2008) and Herberich and List (2012).

[22]Innovations for Poverty Action (IPA) is a US-based non-profit organization that specializes in conducting impact evaluations that aim to inform programs and policies to reduce poverty and improve well-being, primarily in developing countries. See more at www.poverty-action.org.

0.25 and 2.5 hectares.[23] We recruited farmers principally through door-to-door canvassing and, to a lesser extent, at regular farmer meetings. Although we do not have a full census of farmers in the area, based on reports from field staff, we enrolled a large majority of farmers in the target areas who fulfilled the eligibility criteria.

Appendix Section C contains detail about attrition in the experiments. Attrition of farmers overall is greater in the control group (21%) than the treatment group (14%). The attrition improved over time and in the largest and final season, it was 15% in the control group and 8% in the treatment group. This attrition is not trivial and may affect estimates based on the farmer-level randomization. Most of the analyses in this paper are based on within-farmer comparisons taking advantage of the plot-level randomization and the farmers' preferences for insurance over their portfolio. For farmers in the analysis sample, I have damage and output data for 90% of plots and this share is balanced across treatment (90.5%) and control (89.5%) plots (Table H.3 shows the breakdown of plot attrition by season and treatment status). Table 2 shows balance checks across the two stages of randomization. In both cases the randomization is well balanced on baseline observables both at randomization and for the sample of farmers and plots for which we have harvest data. The plot randomization is also clearly orthogonal to the choice of a first-choice plot.

The data come from the following sources: (1) plot choices obtained at enrollment in the study (if a farmer participated in multiple seasons, a new choice was obtained before each season); (2) plot characteristics from a baseline survey; (3) input data from mid-season and follow-up surveys; (4) output and damage data from a follow-up survey; (5) administrative data from the insurance provider; and (6) geospatial data collected by research staff. To obtain a survey measure of the share of harvest lost to the various causes, we asked each farmer how much they lost on each plot to each cause. Because most farmers do not have a good grasp of percentages, we asked about damages in terms of number of sacks of palay (unmilled rice) lost. The most direct way to construct measures that correspond to the model is to compute the percentage of harvest lost to the insured events. I call this the "damage ratio" and define it as damages (total or due to specific causes) divided by harvest plus total damages.[24] In this way, harvest plus total damages are thought of as representing the counterfactual harvest (i.e., the harvest if no damages had occurred). I separate all-cause harvest losses into two components: loss due to typhoons and floods, and loss due to pests

[23]The vast majority of plots fall into this range. The lower bound is an eligibility requirement of the insurance company. Some exceptions from this lower bound were given in the first season. We chose to have an upper bound both because we did not want a large amount of our funds for insurance premiums to be used for a small set of plots and because this seemed more acceptable to the community based on conversations during the pilot phase.

[24]These measures follow naturally from the model. Given that AG is the harvest and AGD is the loss, a natural measure for D is $D = \frac{AGD}{AG} = \frac{AGD}{AGD+AG(1-D)} = \frac{\text{Total loss}}{\text{Total loss+Harvest}}$.

and crop diseases. This distinction is motivated by expectations at the start of the project – that pests and crop diseases would be more preventable than typhoons and floods – and by the fact that the company already uses this categorization.[25] Appendix Section D contains details on the construction of the damage measures and Appendix Section E shows that the findings presented later are robust to variations in the way these measures are constructed.

Table 1 presents summary statistics of the key outcome variables (Table 2 shows summary statistics of baseline variables). Harvest losses due to the various natural hazards are large in this context. During the three seasons of experiments, all-cause harvest losses were 24% on average, with 16% due to typhoons and floods and 8% due to pests and crop diseases. The typical farmer has two to three plots of size 0.6 hectares, with a harvest value of 47,000 pesos per hectare. Per-hectare insurance payouts were about 5000 pesos ($108) on average, or about 650 pesos ($14) per hectare for all insured plots. Conditional on a payout, the average payout amount was 10.3% of the average harvest value.

The baseline survey contains a series of questions on plot characteristics that are used in Section 8 to construct measures of predicted damages by plot. These questions asked, "Compared to your other plots, does this plot have low, medium, or high risk of ______?," where I ask separately for floods, strong wind, rats, and the crop disease tungro. In addition, we asked questions on whether the plot is easy, medium, or hard to drain after heavy rains, compared to the farmer's other plots, and whether the plot is low-, medium-, or high-lying, compared to the farmer's other plots.[26] I combine the questions pertaining to floods (flood risk, low-lying, and hard to drain) into an index (hereafter "the flooding index") by taking the first principal component from a principal components analysis of three binary variables that signify that the plot is high risk for floods, is low-lying, and is hard to drain after floods. Table 1 shows summary statistics of these variables where I have recoded the rat and tungro variables into indicators for medium and high risk and I've omitted the variable on risk of strong wind because it showed very little variation.

6 Results on Adverse Selection and Moral Hazard

In this section I first describe how farmers in the study made their plot choice decisions (based on baseline data). I then empirically estimate the magnitude of moral hazard using data on harvest losses (self reported) and test for adverse selection using data on both harvest losses (again, self reported) and payouts (from administrative data).

[25]The insurance company offers two types of coverage: basic coverage that covers only typhoons and floods, and comprehensive coverage that also includes coverage for pests and crop diseases. The insurance studied in this paper is the comprehensive coverage.

[26]These characteristics were only collected for seasons 2 and 3.

Table 1: Summary statistics of baseline and outcome variables

Variable	Mean	(Std. Dev.)	N
Damages			
All cause harvest loss			
Damage ratio	23.93	(26.9)	1774
Value of damages per hectare	15.5	(19.38)	1774
Harvest loss to typhoons and floods			
Damage ratio	15.94	(23.57)	1774
Value of damages per hectare	10.65	(17.2)	1774
Harvest loss to pests and crop diseases			
Damage ratio	7.98	(17.47)	1774
Value of damages per hectare	4.85	(10.78)	1774
Value of Harvest and Payouts			
Value of harvest per hectare	47.32	(23.08)	1774
Payouts per hectare			
For the sample of insured plots	0.68	(1.9)	690
For the sample of plots with any payout	4.88	(2.32)	96
Payouts as share of average harvest			
For the sample of insured plots	1.44	(4.01)	690
For the sample of plots with any payout	10.32	(4.91)	96
Inputs			
Plot-level expenses for chemicals per hectare (missing set to zero)	0.21	(0.46)	1774
Used pest or disease resistant seeds on plot	0.15	(0.35)	1311
Plot-level fertilizer expenses per hectare	5.23	(3.29)	1238
Fertilizer expenditure with farm-level imputation	5.08	(3.08)	1751
Plot Risk Characteristics			
Flooding index	-0.03	(0.99)	1667
Medium rat risk	0.41	(0.49)	1774
High rat risk	0.2	(0.4)	1774
Medium tungro risk	0.38	(0.49)	1774
High tungro risk	0.14	(0.35)	1774
Other			
Plot size (hectares)	0.59	(0.39)	1774
Owner of plot	0.23	(0.42)	1453
Number of plots (one observation per farmer-season)	2.63	(1.29)	641

The table presents summary statistics of key outcome variables. All variables that indicate value are in 1000's of pesos. In the second fertilizer measure (with farm-level imputation) I impute plot level fertilizer use from farm-level totals by assigning farm-level amounts to plots using the ratio of the plot size to the total farm size as weights.

Table 2: Summary Statistics and Treatment Balance

A. Randomization of farmers

	At Randomization Mean In Insurance Group (A+B)	At Randomization Mean In Control Group (C)	At Randomization Difference (p-value)	Analysis sample Mean In Insurance Group (A+B)	Analysis sample Mean In Control Group (C)	Analysis sample Difference (p-value)
Total enrolled area (hectares)	1.72	1.57	0.15	1.72	1.58	0.13
			(0.09)			(0.18)
Number of enrolled plots	2.89	2.84	0.05	2.89	2.82	0.06
			(0.66)			(0.60)
Education (years)	10.21	10.47	−0.26	10.16	10.45	−0.29
			(0.40)			(0.39)
Age (years)	53.89	52.95	0.94	53.82	53.14	0.67
			(0.34)			(0.54)
Gender (1 = female)	0.17	0.16	0.00	0.17	0.15	0.01
			(0.87)			(0.65)
Observations	606	233		518	179	

B. Randomization of plots
(excludes plots not randomized (Group C and first-choice plots of Group B))

	At Randomization Mean Insured	At Randomization Mean Control	At Randomization Difference (p-value)	Analysis sample Mean Insured	Analysis sample Mean Control	Analysis sample Difference (p-value)
Is first choice plot (1 = yes)	0.33	0.33	0.00	0.34	0.34	0.00
			(0.84)			(0.86)
Area (hectares)	0.59	0.60	−0.02	0.59	0.60	−0.01
			(0.39)			(0.60)
Owns plot (1 = yes)	0.23	0.25	−0.02	0.20	0.22	−0.02
			(0.36)			(0.47)
Flooding index (unit SD)	0.02	−0.03	0.05	−0.02	−0.05	0.04
			(0.37)			(0.49)
High Rat Risk (1 = yes)	0.19	0.22	−0.02	0.19	0.21	−0.02
			(0.21)			(0.44)
High Tungro Risk (1 = yes)	0.15	0.14	0.01	0.15	0.14	0.01
			(0.68)			(0.64)
High Wind Risk (1 = yes)	0.04	0.04	0.00	0.05	0.05	0.00
			(0.91)			(0.83)
Observations	852	852		662	656	

This table shows summary statistics by treatment condition and tests for treatment balance. At the farmer level the right hand part of the table (the analysis sample) is those farmers that did not drop out. At the plot level the right hand part is those plots that have a non-missing value for total damages. Observations are given for the full sample. Some rows are based on a smaller sample due to missing values of the specific variable.

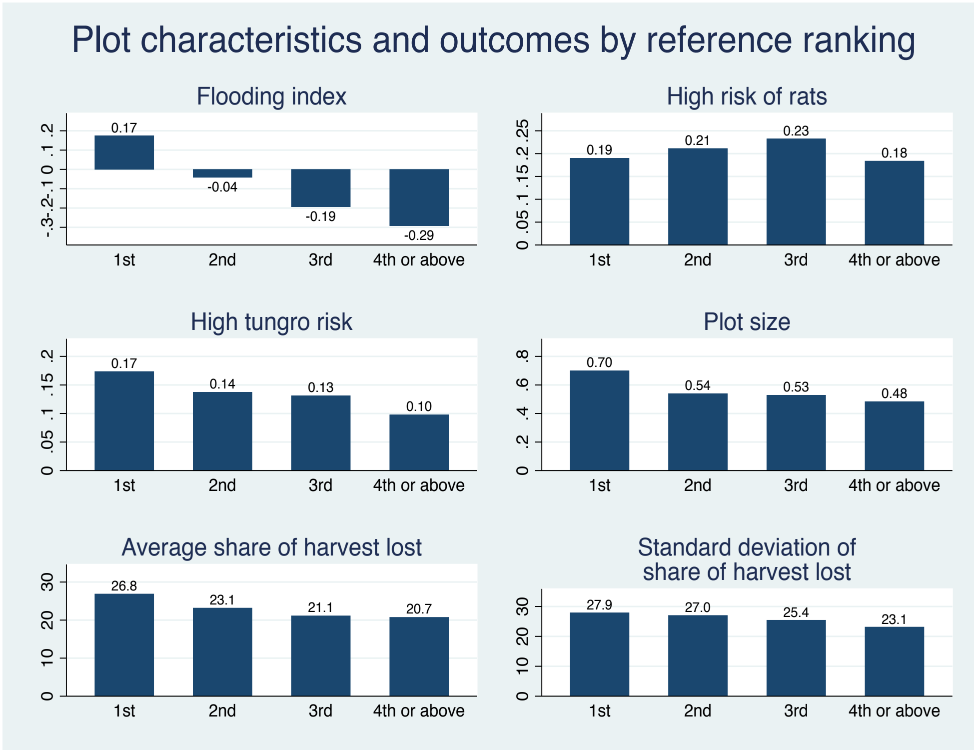


Figure 2: Average share of harvest lost by preference ranking for insurance. The left panel shows the mean and the right panel the standard deviation of the share of harvest lost.

6.1 Preference Ranking of Plots for Insurance

The empirical tests for adverse selection use the fact that by design the farmers were incentivized to reveal their top choice for insurance. The data also include their ranking for their top three choices for insurance. Even though the second and third choices are not incentivized the farmers have little reason to not reveal their preference, so it is instructive to examine how they made these choices. In Figure 2 I investigate these choices (In this figure I exclude first-choice plots of farmers in the choice group so that choice and insurance status are independent). In the first four panels I use baseline survey data, while the last two panels are based on damage data reported after harvest. In the top left panel I report average values of the flooding index by preference rank ordering. It is clear that farmers strongly prefer insurance on plots that they deem at high risk of floods, as indicated by the monotonic relationship from +.17 for first-choice plots down to -.29 for plots outside the top three. In the top right panel I see no pattern of plot ranking based on the risk of rat infestations (even though this risk was reported as being very important in qualitative interviews). In the middle panel on the left I plot the average values of an indicator of the plot having a high risk of harvest losses due to the crop disease tungro, which spread by insects and often brings devastating harvest losses in this area. This risk is clearly an important characteristic that farmers use in their choice: 17% of first-choice plots are deemed (by the farmer) to be at high risk of a tungro infestation compared with 14% and 13% for the second and third choices, and only 10% of the plots outside the top 3. The middle panel on the right shows that, due to the features of the experiment, plot size is an important attribute that farmers use in their choice. This affecs how we understand the estimates of adverse selection later in this section, and I discuss those implications in Section 6.3. In the last two panels I use follow-up data on self-reported damages to plot the average and standard deviation of damages by plot ranking. These panels suggest that farmers indeed know which plots are likely to be damaged and can successfully rank them in order. Both panels show a monotonic relationship from first-choice plots with an average harvest loss of 27% (and standard deviation (SD) of 28) to second- and third-choice plots with harvest losses of 24.4% (SD 27.2) and 21.2% (SD 25.5), and finally to harvest losses of 20.7% (SD 23.1) for plots that are not ranked among the top three.

6.2 Baseline Predictors of Insurance Choice

To get a fuller picture of how farmers in the study select their first-choice plot I estimate a conditional logit model of insurance choice. The outcome variable is a binary indicator of whether the plot was chosen as the farmers' first choice, and the choice is conditional on the portfolio of plots the farmer is tilling in that season. I include the size of the plot (standardized to zero mean and unit standard deviation) and the following risk characteristics of the plot: the flooding index (a standardized variable) and indicators denoting that the farmer evaluated the plot as being at high risk from rats or tungro. Aside from the risk characteristics of the plot, whether the farmer owns the plot, or if not, the type of contractual arrangements the farmer has with its owner, could be an important determinant of plot choice. I capture this dimension by including indicators for land ownership and land contractual arrangements. The categories included are sharecropping, mortgaged in, lent for free and owned.[27] The remaining plots, those under fixed rent contracts, are the reference category in the estimation. In the first season the baseline survey did not include questions on risk characteristics of plots, so data from that season are excluded from the analysis and the estimation is performed on 486 farmer-season portfolios with a total of 1263 plots.

Figure 3 summarizes the results of the estimation. The figure shows parameter estimates as odds ratios and gives 95% confidence intervals. Significance at the 5% level can be visually assessed from the figure by whether the confidence interval includes 1. Three characteristics of the plot are statistically significant in predicting the plot choice: (1) the flooding index,

[27] When a plot is 'mortgaged in' it is tilled by this farmer as interest payment for an outstanding loan to another farmer. Plots are lent for free primarily within families, such as children tilling their parents plots.

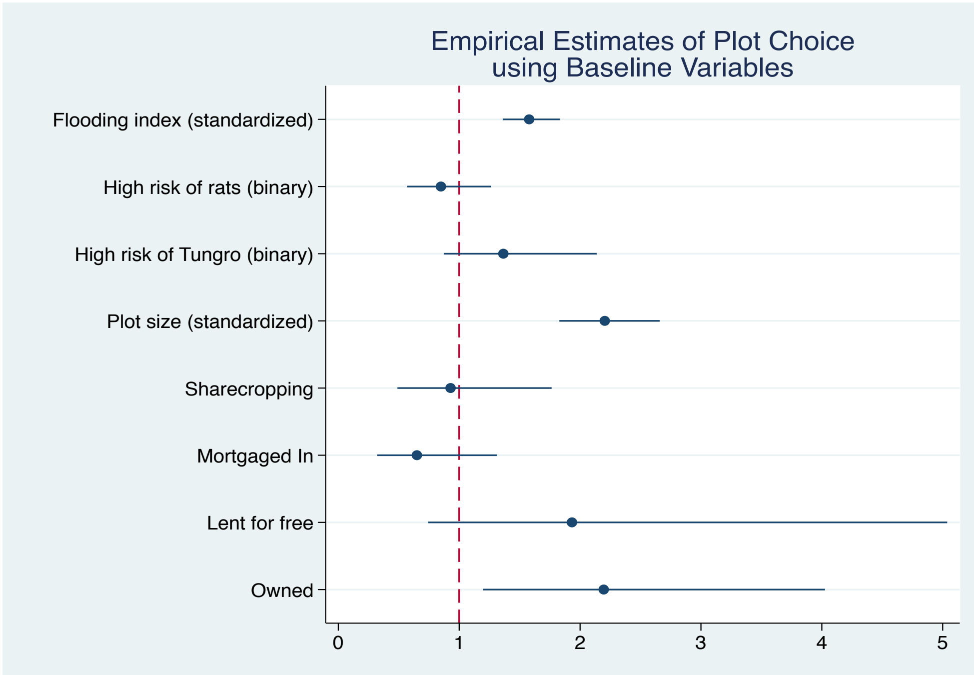


Figure 3: This figure summarizes results of a conditional logit model of plot choice based on baseline predictors.

(2) the size of the plot and (3) whether the farmer owns the plot. I estimate that a plot with a higher flooding index value than another plot by 1 SD is 1.57 times more likely to be chosen, but other risk characteristics are not related to plot choice in a statistically significant way. Likewise, a plot that is 1 SD (0.4 hectares) larger than another plot is more likely to be chosen by a factor of 2.2. Plots that are tilled under fixed rent, sharecropping, or are mortgaged in are chosen at similar rates but those owned by the farmer are clearly favored (the estimated odds ratio is 2.2). Plots lent in for free also seem to be favored but this effect is statistically insignificant.

The strong association between the flooding index and insurance choice is additional evidence that the farmers are engaged in a substantial amount of adverse selection. In the next section, I confirm this finding using data on damages and payouts and test for and estimate the degree of moral hazard.

6.3 Main Empirical Specification and Results

The main empirical specification is a within-farm specification (that is, including farm-season fixed effects) with indicators for insurance status and first-choice plot:

$$D_{ij} = \beta_0 + \beta_1 \alpha_{ij} + \beta_2 C_{ij} + \beta_4 A_{ij} + \lambda_i + \epsilon_{ij} \tag{5}$$

The outcome variables (damages, payouts, or plot characteristics) are described in the next section. Here α is an indicator for insurance coverage, and C is an indicator for the plot chosen as the farmer's first-choice plot. A is the area (size) of the plot in hectares (centered at the sample mean), and λ_i is a farm-season fixed effect. The reason for the additional area control is a possible correlation between area and plot risk characteristics. If A is positively correlated with θ_{ij} (inherent riskiness) or ψ_{ij} (cost of effort), the additional control for area guards against the mistake of attributing selection on area to selection on other characteristics.[28]

I estimate this equation excluding first-choice plots of farmers that were in the choice group. This approach means, given the randomization of insurance, that plot choice (and the indicator C_{ij}) is independent of the insurance allocation (α_{ij}).[29] This approach provides unique variation in the data that can be used to separately identify adverse selection and moral hazard. Given the randomized allocation of insurance in this sample, the β_1 coefficient captures the effect of insurance on a plot relative to uninsured plots in the farmer's portfolio (since farmer-season fixed effects are included). When the outcome variable is damages, a positive β_1 coefficient suggests moral hazard behavior in preventing damages on insured plots. The β_2 coefficient likewise captures the degree to which damages (or payouts) are higher on first-choice plots relative to other plots in the farmer's portfolio (or, in the case of plot characteristics, more adverse). I can therefore test for adverse selection by evaluating whether this coefficient is positive.

Figure 4 summarizes the results of empirically estimating Equation 5. The figure reports parameter estimates and 95% confidence intervals for β_1 (left panel) and β_2 (right panel) for four outcome variables (listed to the left of the figure). In each case the confidence interval is constructed using standard errors that are corrected for spatial correlation according to the spatial GMM method in Conley (1999). These results are also reported in Columns 1, 3, 5 and 7 in Table 3.

The specification above implicitly assumes a constant treatment effect of the insurance

[28] Empirically, whether the plot size is included as a control has very little impact on the results (adverse selection estimates are about 5% higher without this control) and adding higher order terms of plot size has no effect. The effects reported are also not driven by a large shift in per-hectare harvest: if I replace the outcome variable with per-hectare harvest then I find that first-choice plots have 1.8% lower, and insured plots 0.6% higher, harvest than other plots (these specifications include a control for area). In theory, we would expect the harvest to be lower on insured plots due to moral hazard but in practice (with finite sample sizes) it is hard to detect this effect given that damages due to pests and crop diseases are only a small part of the process that determines overall harvest.

[29] As a reminder, for those not in the choice group the insurance is allocated at random using block randomization within the farm. Farmers in the choice group get insurance on their first-choice plot and the rest of the plots are allocated insurance as though their farm consisted only of the plots excluding the first-choice plot. Therefore, excluding the first-choice plot of the choice group provides a sample of plots for which insurance status is allocated at random.

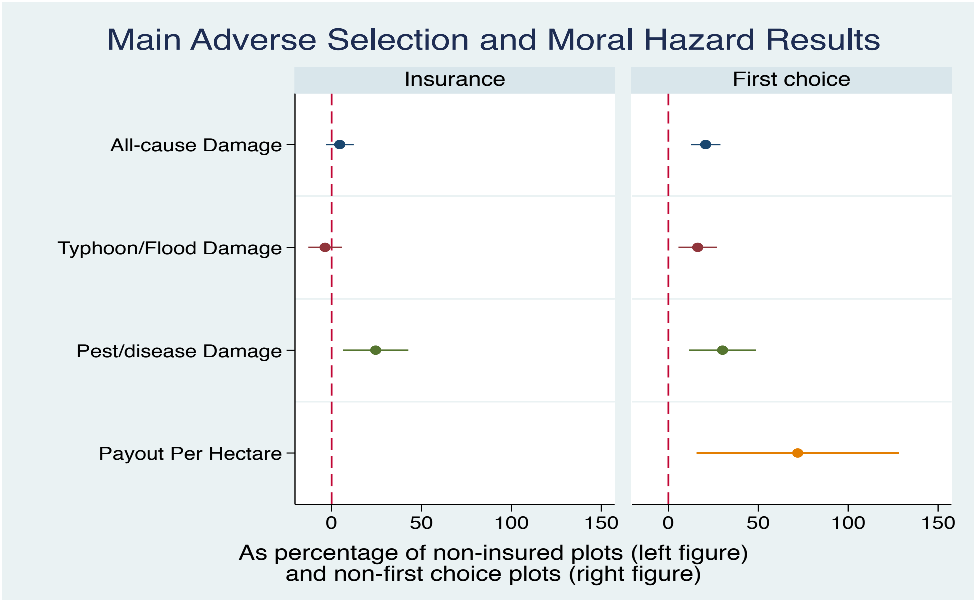


Figure 4: This figure summarizes results of regressions based on Equation 5. Each row represents a separate regression, differing only in the outcome variable. Estimated coefficients and 95% confidence intervals for β_1 (insurance) are shown in the left panel scaled as a percentage of non-insured plots and for β_2 (first choice) in the right panel scaled as a percentage of non-first-choice plots. The estimations with damages as an outcome variable (the first three rows) are based on 1739 observations with 695 farm-season fixed effects in which I use the full sample except that I exclude first-choice plots of farmers in the choice group. The last estimation (payout per hectare) is based on 691 insured plots and, although all 492 farmers with some insurance are included in the regression, the identification is based on only 92 farmers who had both their first choice plot and at least one other plot insured. Standard errors are corrected for spatial dependence using the method developed by Conley (1999).

coverage across first-choice and other plots. I can relax this by including interactions between choice and insurance coverage. Given the design of the experiment, this interaction terms identifies *selection on moral hazard* since it estimates how much greater the moral hazard effect is on first choice plots compared to other plots. Columns 2, 4 and 6 in Table 3 report on models with these interactions included. Unfortunately the data has low statistical power to test whether these interactions are present but I develop and perform an alternative test for this effect in Section 8.

6.3.1 Moral Hazard Results

I first describe the findings in the left side panel of Figure 4, which reports the coefficient on insurance allocation for a plot in the preceding regressions. The coefficient on insurance identifies the causal effect of insurance on the difference in farming practices between insured and uninsured plots. I find evidence for moral hazard in preventing pest and crop disease damage but not in preventing typhoon and flood damage. Damages from pests and crop diseases are on average 1.66 percentage points (21.5%) larger on insured plots compared to uninsured plots of the same farmer. This finding is robust to using alternative outcome variables (such as using the value of harvest lost due to these specific causes, or using the log of this value) and to including of the full set of plot controls. These findings suggest that moral hazard accounts for $\frac{21.5}{100+21.5} = 18\%$ of insurance payouts under the pest and crop disease coverage and 7% of all payouts under the comprehensive insurance coverage. This moral hazard effect is observed even though the insurance coverage is far from complete, suggesting that moral hazard is a significant constraint to offering insurance contracts with higher coverage levels.

There are at least two issues to consider in interpreting these findings. First, since the damages are self-reported farmers may overstate damages on insured plots. The fact that we do not see any moral hazard effect on typhoons and floods is evidence against this hypothesis since there is no reason to expect farmers to overstate less on that dimension. In addition, as we will see in Section 7, farmers appear to use less fertilizer on insured plots, which (as we saw in the model) is consistent with moral hazard behavior. Second, this estimate may overstate the moral hazard effect if there are important spillovers to other plots in the farmers portfolio. These are discussed in Section 7.3.

6.3.2 Adverse Selection Results

In the results reported in the right panel, I estimate that total damages are 4.6 percentage points (20%) greater on first-choice plots compared to other plots, which have a damage rate of 22.2%. This outcome is in equal parts due to higher damages from typhoons and floods (2.45 percentage points) and pests and crop diseases (2.1 percentage points). Both of these estimates are statistically significant and suggest that first-choice plots have 16.3% higher damages from typhoons and floods and 29.2% higher damages from pests and crop diseases. Finally, in the last row of Figure 4 (and Column 7 of Table 3), I report estimates of Equation 5 on the sample of insured plots using payouts as an outcome variable. The outcome variable here is payouts per hectare as a share of the average harvest value per hectare (for all plots). I find a statistically significant difference, with first-choice plots having 72% greater payout than other plots.

The evidence on damages and payouts, along with the evidence from the last section on the associations between baseline variables and insurance choice, shows that the farmers have substantial private information about the risk profiles of their land and are able to leverage this information in their relationship with the insurance provider. To interpret the magnitudes and understand better how farmers are making these decisions it is worth considering several key factors that influence the plot choice decision, namely risk preferences, geographic heterogeneity and the tradeoff between plot size and risk of damage.

First, because farmers in the study do not purchase insurance they may, as a group, be less risk averse than those farmers who would purchase insurance in the market. This may complicate interpretation if individuals with a high degree of risk aversion, and therefore higher demand for insurance, tend to farm low-risk land or work harder to prevent damages. This could possibly result in what de Meza and Webb (2001) term *advantageous selection*.

To investigate how the findings might apply to a more risk averse group, I use a question from the baseline survey that asked farmers how willing they are, on a scale from 1 to 7, to take risks on their farms. I categorized 27% of the farmers as having relatively high risk aversion based on this measure. I use this measure in two ways. First, I estimated a simple regression of damages on risk aversion, reported in Table H.6. The risk aversion measure is not correlated with typhoon and flood damages, but pest and crop disease damage is lower on the farms of more risk-averse farmers. This relationship holds and is almost identical after controlling for age, education, and the number of plots. This outcome is likely due to risk-averse farmers taking greater care to prevent damages from pests and crop diseases. Although this simple analysis is subject to bias due to omitted variables, this pattern is consistent with the potential for risk preferences to reduce or eliminate the adverse selection in the insurance for pests and crop diseases or even to induce advantageous selection. This could be the case if, for instance, the true effect of risk aversion is much stronger but I estimate a smaller effect because of measurement error in risk aversion. At the same time, there appears to be little evidence of a risk preference effect in the insurance for typhoons and floods. Next, I estimated models of the form

$$D_{ij} = \beta_0 + \beta_1 C_{ij} + \beta_2 C_{ij} \times Z_i + \beta_3 A_{ij} + \lambda_i + \eta_{ij} \tag{6}$$

where D_{ij}, C_{ij}, A_{ij} and λ_i are as before, but I now include an interaction term between first choice and a farmer- or farm-level variable Z_i. I estimate three models, varying the outcome between overall damages, typhoon and flood damage or pest and disease damage, and here Z_i is the risk aversion measure above. Here η_{ij} is a disturbance term, and I cluster standard errors at the level of the farm-season (rather than using the spatial clustering since the variation of the interaction variables is at the farmer level make within-farm correlations a greater concern).

The findings are reported in Figure 5. In the three graphs on top, no interaction with risk aversion is apparent for typhoon and flood damage but a substantial negative (and statistically significant) interaction effect is present for pest and disease damage. That is, I find less adverse selection in pest and disease damage among the more risk-averse farmers. In fact, this negative interaction effect is large enough to cancel out the previous adverse selection findings so that I find no adverse selection in pest and disease damage for risk-averse farmers. This pattern again supports the view that advantageous selection based on

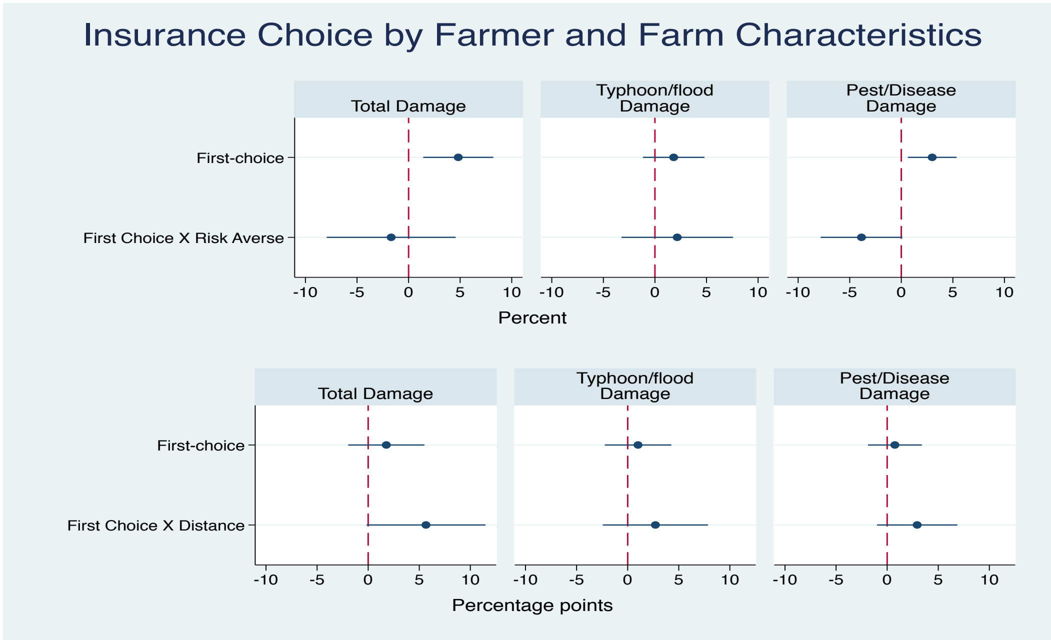


Figure 5: This figure summarizes results of regressions based on Equation 6. The outcome variable are the usual share of harvest losses due to all causes (left), typhoons and floods (middle) and pests and crop diseases (right). The risk aversion measure is an indicator based on a baseline question of how willing the farmer is in taking risks on her farm. The "Distance" variable is an indicator that is one if largest distance between two plots on the farm falls above the median for such distances across all farms. The top three panels are based on 670 farmers with 1654 plots and the bottom three on 612 farmers with 1497 plots (due to missing observations in the risk aversion and distance measures). The confidence intervals are at the 95% level. Standard errors are corrected for spatial dependence using the method developed by Conley (1999).

risk preferences may ameliorate the adverse selection problem for insurance against pests and crop diseases but not for insuring typhoon and flood damage.

An important heterogeneity in the data is that some farmers have plots in close proximity to each other while others have more spread out farms. We can use this to get a sense of the risk heterogeneity that the farmers are able to take advantage of in selecting plots for insurance. To investigate, I again use the specification in Equation 6 but replace the Z_i variable with an indicator for how spread out the farm is (it is equal to one if the distance between the two plots furthest apart is larger than the median for the sample). In the three graphs at the bottom of Figure 5 I show that there is greater adverse selection on farms that are more spread out. I estimate that for farms that are less spread-out, the adverse selection effect in total damages is 1.8 versus 7.4 on more spread-out farms. This suggests that the risk heterogeneity that the farmers can take advantage of is larger across different parts of the pricing area than it is across the plots of the typical farm. A natural question here is whether the insurance company can collect better information and price these contracts at a finer level (or even at the plot level). Data on how much it would cost to obtain such information are not available but the type of information that can be collected profitably is substantially constrained by the small size of the premium payments for a typical plot.

Finally, an important issue derives from the fact that the insurance was given for free for a specific plot rather than a specific acreage (The latter would have either necessitated a revised insurance contract and altered procedures by the company, adding substantial complexity, or it would have required matching payments from the farmers, requiring a much larger experiment). The farmers therefore have an incentive to select a large plot as their first choice so the tradeoff between size and risk of damage may influence the adverse selection estimates reported in Figure 4. To get a sense of how the tradeoff between risk and plot size affects the adverse selection estimates I performed a simple simulation exercise. The details and results are described in Appendix F. The results imply that if the insurance had been awarded in a way that did not reward choosing a larger plot then we would expect the difference in damages between first choice plots and other plots to be in the range of 38-56% larger.

6.4 Contract Redesign

One possible adjustment in the contract would be to focus on catastrophic losses, for example, to only pay out if losses exceed $\frac{2}{3}$ of the expected harvest. This approach would save on verification costs and possibly improve demand through lower prices and focus on the events with the highest utility cost. This approach would, unfortunately, likely lead to even more adverse selection. In fact, using the specification in Equation 5 I estimate (see Table 4) that 6.7% of first choice plots versus 4.2% of other plots have catastrophic typhoon or flood losses (above $\frac{2}{3}$). The first-choice plots therefore have 60% higher chance of such catastrophic loss. This is compared to only a 7% higher chance of typhoon or flood loss above 10%. The same pattern can be seen in the pest and crop disease insurance. Looking only at catastrophic losses, which I now define as losses above $\frac{1}{3}$ since the average is much lower, I find that first-choice plots are 36% more likely to have such damage and insured plots are 34% more likely. This is in contrast to 24% and 11% for damage above 10%, respectively. Taken together it is clear that the company faces a very difficult adverse selection problem and that shifting to a more catastrophic coverage would exacerbate both the adverse selection and moral hazard problems.

7 Moral Hazard and Investment

In this section I examine the impact of insurance on farming decisions using measures on inputs (fertilizer, pesticides, seeds), outputs and damages. I start by estimating models similar to these in the last section with an indicator for insurance coverage and farmer-

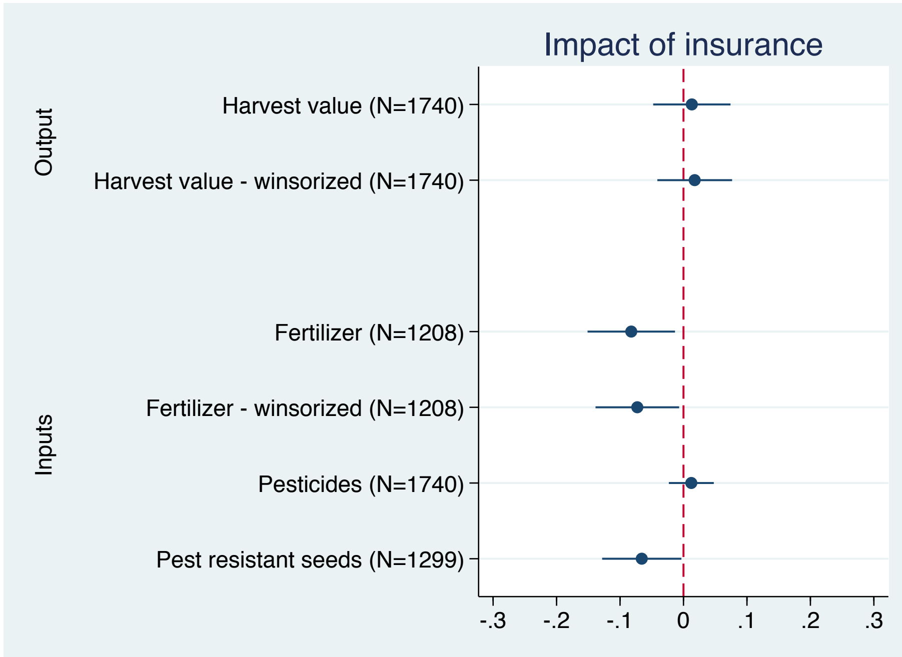


Figure 6: This figure shows the estimated β_1 (insurance) coefficients and 95% confidence intervals from estimating Equation 7 for a series of outcome variables (listed on the left). When outcome variables are marked as winsorized they have been winsorized at the 95th percentile (one sided). Each outcome variable is standardized. Standard errors are corrected for spatial dependence using the method developed by Conley (1999).

season fixed effects. These models show how farmers treated their insured and uninsured plots differently. But, since the uninsured plots may be affected by insurance coverage on other plots in the portfolio, I also estimate models in which I drop the farmer-season fixed effect and include indicators for insurance at the plot level and for getting any insurance (at the farmer-season level). These models allow me to test whether decisions on an uninsured plot are affected by insurance coverage on one of the farmer's other plots.

7.1 Investment

An important feature of the insurance contract is that it does not provide coverage for yield-enhancing investment such as fertilizer because the payout is based on the share of the harvest lost instead of the absolute loss. Total loss for two farmers, one headed for a bumper crop due to heavy fertilizer use and the other for a lackluster harvest because of low investment, would yield the same payout on a per-hectare basis. As I show in the model section, given the moral hazard incentives in the insurance contract, this feature implies that farmers have an incentive to use less variable investment such as fertilizer on insured plots. We might therefore expect to see lower fertilizer use on insured plots and, because of this and because of increased damages due to moral hazard, we might also expect lower output.

I Figure 6 I report results of regressions of the form

$$O_{ij} = \beta_0 + \beta_1 \alpha_{ij} + \beta_2 A_{ij} + \lambda_i + \epsilon_{ij} \tag{7}$$

where O_{ij} is the outcome (or input) on plot j on farm i, α is insurance coverage, and λ_i's are farm-season fixed effects. For easier reporting I standardized all outcome variables reported in this figure. For each outcome variable, I give the point estimate (in standard deviation units) and 95% confidence intervals computed using spatially clustered standard errors.

I find no effect of insurance on the value of harvest, but I find a 5% reduction in average fertilizer use ($p = 0.04$). To temper the effect of possible outliers, I also estimated these models after winsorizing the outcome variables. When winsorizing at the 95th (shown) and 90th percentiles, I find a reduction of 3.6% and 3%, respectively, both significant at the 10% level. The insurance appears to cause a small reduction in fertilizer use. In contrast to recent findings for index insurance, the data are clearly inconsistent with insurance resulting in an *increase* in variable investment.

7.2 Mechanisms of Moral Hazard

Farmers can manage damages from pests and crop diseases in multiple ways, both individually and together with neighboring farmers. Individually, the farmer can choose pest- or disease-resistant seeds and monitor plots closely, removing infected or infested plants and using pesticides, insecticides, rat poison and other chemicals to both prevent or respond to an outbreak. Collectively neighboring farmers can limit pest and disease damage through coordination, including synchronization of planting dates.

Looking at Figure 6 again, the next to last outcome variable is total expenditure on chemicals (pesticides, insecticides and rat poison) to prevent insured damages due to pests and crop diseases. Because of moral hazard, farmers might be expected to reduce these expenditures on insured plots, at least to the degree that they are used to prevent outbreaks. Once an outbreak is observed, given that the insurance is partial, farmers likely have strong incentives for applying these chemicals regardless of whether the plot is insured. I find no difference in this expenditure between insured and uninsured plots.[30] This finding could be either because this is not an important mechanisms for moral hazard in this context or because the measured expenditures are underestimated because of recall bias.[31] The final

[30] I similarly find (but do not show) no difference when limiting this measure to expenses applied as a preventative (before any outbreak is observed).

[31] Some farmers could only give expenditure at the farm rather than plot level and these expenditures are not included in the measure reported in Column 3. The expenses reported by plot are about 0.5% of the average harvest value.

outcome variable in the figure is an indicator variable that is 1 if the farmer reported in a mid-season survey (right after planting and before realizing damages or harvest amounts) that the seed used on this plot was chosen in part because it is resistant to pests, insects or diseases. This measure has some limitations compared to a more objective measure of pest and disease resistance of the seed chosen, but it has the advantage of being a measure of the farmers' beliefs about the seed type chosen. I find that farmers report choosing pest- and disease-resistant seeds on 15% of control plots but 13% of insured plots, a statistically significant reduction of 14%.

The reduction in pest- and disease-resistant seeds is one additional piece of evidence suggesting that the increase in pest and crop disease damage on insured plots observed in the last section arises from moral hazard and not chance or reporting bias. However, given the small absolute change in the type of seeds used, this mechanism is unlikely to be the main driver for the observed moral hazard effect.

Perhaps the most important mechanism – the day-to-day care, managing water and fertilizer, monitoring for outbreaks and removing infected and infested plants – is very hard to measure. The agricultural surveys included modules for labor allocation and the available data allows estimates of large labor costs such as those for planting and harvesting, applying fertilizer and chemicals, and general monitoring, but these modules were not sufficient to measure adequately day-to-day care and I therefore omit testing directly for changes in labor allocation.

7.3 Farm-level Insurance and Background Risk

Insurance was allocated at two levels in the experiments (across farms and across plots within farms). This design permits testing for whether insurance on one plot affects investments on other (uninsured) plots on the farm. This can happen through, for instance, scale economies or reduction in background risk.[32]

In Figure 7, I report results of regressions of the form

$$O_{ijs} = \beta_0 + \beta_1 \alpha_{ijs} + \beta_2 T_{is} + \beta_3 A_{ijs} + \omega_s + \epsilon_{ijs} \tag{8}$$

where O_{ijs} is the outcome (or input) on plot j on farm i in strata s, α_{ijs} is insurance coverage on plot j, T_{is} is an indicator for farmer j in strata s being in the insurance group, and ω_s's are (farm-level) randomization strata fixed effects. For easier reporting, I standardized all

[32] One example of the scale economies channel is if there is a fixed cost to going to market and purchasing inputs. If one plot is insured and the farmer consequently does not use pesticides or fertilizer on that plot, then the fixed cost of purchase is no longer shared across the two plots. As a result, in some cases, the farmer might also omit these inputs on the uninsured plot.

Impact of Insurance

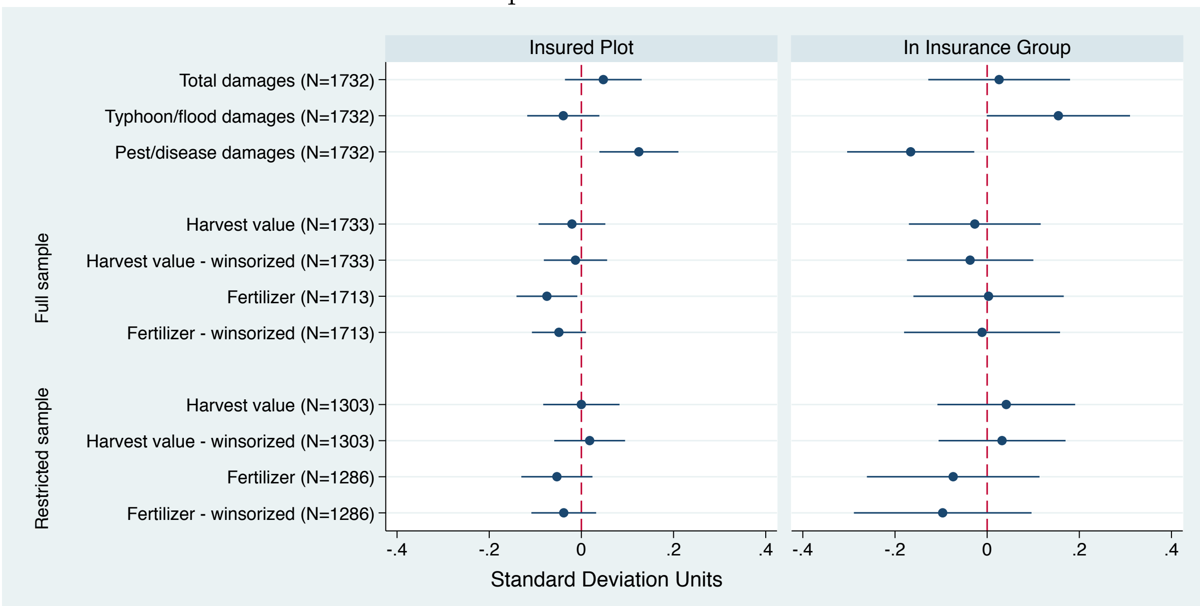


Figure 7: This figure reports estimations of Equation 8. Estimates and 95% confidence intervals for β_1 are reported in the left panel and for β_2 in the right panel. When outcome variables are marked as winsorized they have been winsorized at the 95th percentile (one sided). These regressions include 87 (in some cases 86) fixed effects for randomization strata. Standard errors are clustered at the farm-season level.

outcome variables reported in this figure. Because the variation in T is at the farm-season level, I am more concerned about correlated outcomes within farms than spatial correlation so I cluster standard errors at the randomization strata level. The figure reports the point estimate (in standard deviations) and the 95% confidence interval for each outcome variable. In principle we might also want to apply a spatial standard error correction but there are currently no methods to do both at the same time.

Since T is randomized within the strata and α within the farm, β_2 identifies the difference in the outcome of uninsured plots of treatment (insured) farmers versus the plots of control (uninsured) farmers. It therefore identifies the effect of any insurance at the farm level on uninsured plots. Likewise, $\beta_2 + \beta_1$ identifies the difference in the outcome of insured plots compared to plots of the control (uninsured) farmers, identifying the combined effect of (some) farm-level insurance coverage and insurance on this specific plot. However, the identification of β_2 is complicated by nontrivial attrition of farmers in the experiments and particularly by the control group having higher attrition (21%) than the treatment group (14%). This attrition is not correlated with farmer demographics (see Table 2) but a key concern is whether it is based on realizations of damages.

The first three models of Figure 7 (from the top) report the results of estimating equation 8 with damages (total, typhoon and flood, pest and crop diseases) as outcome variables. The estimates for β_1 are in the left panel and those for β_2 are in the right panel. I estimate β_2

to be close to zero for all damages but positive for typhoon and flood damage, and negative for pest and crop disease damage. Both of these estimates are statistically significant. The typhoon and flood effect does not fit with a moral hazard interpretation given the findings of no within-farm differences across insured and uninsured plots and given that much of this damage is hard or impossible to prevent. The negative effect on pests and crop diseases is also hard to explain based on theory. An important possible interpretation of these findings is that some farmers allocated to the control group who suffered high losses from typhoons and floods refused the follow up surveys out of disappointment. This possibility may explain the estimated β_2 coefficient for typhoons and floods. It may also partly explain the pest and crop disease effect since these are negatively correlated (the raw correlation in the control group is -0.15). Another possibility is that the standard errors for β_2 are underestimated, for instance because I do not correct for spatial dependence in these models (since methods to do that while also clustering errors within the farm are not currently available).

Because of the above suspicion of differential attrition (at the farm level) based on realized damages I estimate equation 8 for output and fertilizer inputs in two samples. Models 4 through 7 (from the top) in Figure 7 use the full sample while the next four models use a sample that is limited to farmers in the bottom three quarters on the distribution of typhoon and flood damage on their farm (loosing less than 38%). If farmers with very high typhoon and flood damage are attritting because of disappointment, then this sample would exclude many farmers in the treatment group that would have attritted had they been allocated to the control group.

It was quite common for framers to be unable to report fertilizer use by plot. In these cases we recorded total fertilizer use on the farm. For the analysis in this section we use a measure of fertilizer use that includes an imputation where I assign fertilizer use to plots using the ratio of plot size to total farm size as weights when the farmer could only give total fertilizer expenditure.

For the full sample, all estimates for harvest value and fertilizer expenditure of β_2 are close to zero. For the restricted sample, none of the estimates is statistically significant compared to zero but the point estimates for fertilizer are negative (about 0.07-0.10SD below zero). Taking these together, I do not have evidence to reject the hypothesis that farming decisions on uninsured plots of treatment farmers are unaffected by the treatment. However, this conclusion could be due to lack of power, particularly if we look at the fertilizer expenditure in the restricted sample. Interestingly, in the restricted sample $\beta_1 + \beta_2$ is statistically significant (at the 10% level) compared to zero for fertilizer expenditure both using the raw measure and after winsorizing at the 95th percentile ($p = 0.059$ in the former and $p = 0.048$ for the latter). This finding is consistent with the interpretation that the insurance coverage reduces fertilizer investment. However, these conclusions must come with the caveat that the β_2 estimates (even in the restricted sample) may be biased due to attrition based on realized damages.

8 Selection on Moral Hazard

In this section, I test for overall adverse selection and separately for selection on "baseline risk" and for "selection on moral hazard" using measures of predicted damages. The main idea for the decomposition is presented in Figure 1b. I first compute predicted damages based on baseline information separately for insured and uninsured plots (for farmers in the fully random group). Then, I identify overall adverse selection by comparing the predicted damages for insured first-choice plots to other insured plots of the same farmer – that is, effect (a) in Figure 1b. I can disentangle adverse selection into two effects: (1) selection on baseline risk by comparing predicted damages on uninsured first-choice plots to predicted damages on uninsured other plots – that is, effect (b) in Figure 1b, and (2) selection on intended moral hazard by taking the difference in predicted change in damages, when moving from being uninsured to being insured (moral hazard), between first-choice plots and other plots – that is, effect (c) minus effect (d) in Figure 1b.

In Table H.8 I show that plot characteristics observed by me through a baseline survey predict 30% of harvest losses (these plot characteristics are described in Section 5). These characteristics are not observed by the insurance company, and in this section I use them as a proxy for the full information set that the farmer has about each plot. Some of these characteristics (or their proxies) might in principle be observable by the insurance company. However, the company currently does not condition prices on any plot characteristics, likely because they are too expensive to collect. Instead the company sets prices regionally and excludes high-risk areas. Although the insurance contract studied is not developed in a competitive market, the fact that these characteristics are not collected is suggestive evidence that they are expensive to collect compared to the premiums that could be sustained in this market.

8.1 Empirical Approach

I now use these variables to construct a measure of predicted damages, which I then use to decompose the selection into the two conceptually distinct components.

8.1.1 Adverse Selection without Selection on Moral Hazard

First, I consider the case in which the farmer does not anticipate changes in effort due to insurance coverage, either because the cost of effort is very high (low) and the farmer therefore exerts no (full) effort in any scenario, or because the farmer is myopic and does not take the anticipated effort response into account when selecting a plot for insurance. In Section 4.3, I found that in this case the farmer chooses the plot that maximizes expected payouts. That is, given that expected damages according to the model when no effort is applied are $\frac{1}{2}A_j\theta_j$, the farmer chooses the plot that has the highest $A_j\theta_j$ (area times baseline risk). I will test for adverse selection by comparing this model to the null hypothesis of no adverse selection, where farmers instead simply choose their largest plot. Based on the per-plot utility output derived in the model (Equation 16), the utility of insurance on plot j is $v_j^* = u_j(\alpha_j = 1) - u_j(\alpha_j = 0) = cA_j\theta_j$ where $c = \frac{1}{2}L$ is constant. Let $\bar{\theta} = \frac{1}{N}\sum_{j=1}^{N}\theta_j$. We can then decompose this utility into

$$v_j^* = cA_j\bar{\theta} + cA_j(\theta_j - \bar{\theta}) \tag{9}$$

Now, under the assumption that the farmer ignores any effort response to insurance, the farmer chooses insurance based on $E\left[D_j|\theta_j\right] = \frac{1}{2}A_j\theta_j$ and I can empirically proxy for the utility by $\hat{u}_j = A_j\hat{E}\left[D_j|\theta_j^{obs}\right]$ where θ_j^{obs} is the portion of risk observable to me based on the baseline characteristics. To empirically estimate 9, I use a conditional logit with the choice conditioned to the portfolio of each farmer (McFadden, 1974). The estimation equation is

$$Prob(C_{ij} = 1) = \Lambda(\alpha_0 + \alpha_1\hat{E}\left[D|X, I = 1\right] + \alpha_2 A_{ij}) \tag{10}$$

where Λ is the conditional logit function and $C_{ij} = 1$ if farmer i chose plot j as her first choice.[33] To test the model I include a term for area because if no adverse selection is present, farmers are predicted to choose their largest plot. Here $\alpha_1 > 0$ provides a test for adverse selection.

8.1.2 Decomposition of Selection on Baseline Characteristics

I now allow that farmers may be sophisticated and take into account their endogenous provision of effort on insured plots. Let $\hat{e}_j^I$ be the farmer's optimal choice of effort on plot j if the plot is insured, and likewise $\hat{e}_j^0$ for an uninsured plot. Now, again based on Equation

[33] Strictly the third term should be multiplied by the expected damages for the average plot, $\hat{E}\left[D|\bar{X}, I = 1\right]$, but this does not affect the estimate of α_1.

16, the utility of insurance coverage on plot j can in this case be written as

$$v_j^{**} = u_j(\alpha_j = 1) - u_j(\alpha_j = 0) = \overbrace{\underbrace{\frac{1}{2}A_j\theta_j(1-\hat{e}_j^0)L}_{v_b} - \frac{\rho}{12}\left[(1-L)^2 - 1\right]A_j^2\theta_j^2(1-\hat{e}_j^0)^2}^{\text{Utility from coverage of inherent risk}}$$

$$+ \underbrace{\overbrace{\frac{1}{2}A_j\theta_j(\hat{e}_j^0 - \hat{e}_j^1)L}^{v_m}}_{\substack{\text{Utility of coverage} \\ \text{for moral hazard}}} + \underbrace{\frac{\rho}{12}A_j^2\theta_j^2(1-L)^2\left[(1-\hat{e}_j^0)^2 - (1-\hat{e}_j^1)^2\right]}_{\substack{\text{Utility loss due to higher} \\ \text{variance through lower effort}}} + \underbrace{A_j\psi_j(\hat{e}_j^0 - \hat{e}_j^1)}_{\substack{\text{Utility gain from} \\ \text{saved effort}}} \quad (11)$$

I can proxy for the first and third terms (labelled v_b and v_m above) in this utility from data and use this to test for the presence of selection on the ability to engage in moral hazard. That is, if I define $v_b = \frac{1}{2}A_j\theta_j(1-\hat{e}_j^0)L$ and $v_m = \frac{1}{2}A_j\theta_j(\hat{e}_j^0-\hat{e}_j^1)L$ then the empirical analog of these expressions are: $\hat{v}_b = A_{ij}\hat{E}\left[D|X, I=0\right]$ and $\hat{v}_m = A_{ij}(\hat{E}\left[D|X, I=1\right] - \hat{E}\left[D|X, I=0\right])$. To test separately for the two types of selection I estimate a conditional logit of the form:

$$\begin{aligned}\Lambda(C_{ij}) &= \alpha_0 + \alpha_1\hat{v}_b + \alpha_2\hat{v}_m + \alpha_3 A_{ij} + \epsilon_{ij} \\ &= \alpha_0 + \alpha_1\hat{E}\left[D|X, I=0\right] + \alpha_2(\hat{E}\left[D|X, I=1\right] - \hat{E}\left[D|X, I=0\right]) \\ &\quad + \alpha_3 A_{ij} + \epsilon_{ij}.\end{aligned} \quad (12)$$

Now $\alpha_1 > 0$ provides a test for selection based on what could be called baseline risk, that is, on $\frac{1}{2}\theta_j(1-\hat{e}_j^0) = E\left[D|I=0\right]$. The last term in the Equation 11 is positive if and only if $\alpha_2 > 0$. Therefore, given that the cost of effort is positive ($\psi > 0$), $\alpha_2 > 0$ provides a test for selection based on the plot-specific utility of saved effort.

8.1.3 Predicted Damages Based on Baseline Characteristics

To empirically estimate 10 and 12, I must first obtain empirical estimates of predicted damages $\hat{E}\left[D|X, I=0\right]$ (for uninsured plots) and $\hat{E}\left[D|X, I=1\right]$ (for insured plots). In Table H.9 I estimate models of the form:[34]

$$D_{ij} = \beta_0 + \beta_1 X_{ij} + \beta_2 X_{ij}1(\text{dry season}) + \lambda_i + \eta_{ij} \quad (13)$$

separately for insured and uninsured plots of farmers in the pure randomization group (Group A). Here X indicates the baseline characteristics used for prediction (the flood index and

[34]The estimates given in this table are for the full sample, but to obtain bootstrapped standard errors, this prediction is repeated for each bootstrap sample.

indicators for medium or high risk from rats or tungro), λ_i's are farmer-season fixed effects and η_{ij} is an error term. I then use the predicted values from these two regressions as my measures of $\hat{E}\left[D|X, I=1\right]$ and $\hat{E}\left[D|X, I=0\right]$.

8.2 Results on Estimated Selection Effects

Using these predicted damages, I can now empirically estimate equations 10 and 12. Table 5 presents these results. In each case, I estimate a conditional logit model with controls for plot size, land ownership and contractual arrangements. For all estimations in this table, I perform 500 bootstrap replications to estimate the predicted damages and the choice models. Although I use only farmers who were in the full randomization group (Group A: Received insurance on half of plots at random) to estimate the predicted damages, I use the full sample when estimating the choice models presented in this table (since the choice is made ahead of the randomization).

In Column 1, I estimate equation 10 and find strong evidence for adverse selection. A 1 percentage point increase in predicted damages increases the odds of a plot being chosen by 8%. In Column 2, I estimate equation 12 and find strong evidence for adverse selection on baseline risk (suggesting again 8% increased odds). The estimate in the third row of Column 2 is consistent with selection on moral hazard. Farmers are estimated to have a 7% increased odds (significant at the 10% level) of choosing a plot for each percentage point increase in the difference of expected damages between insured and uninsured plots.

These findings imply that farmers select not only on the baseline risk of plots (that is, $\theta(1-\hat{e}_0)$ in the model) but also on the cost of effort since a positive α_3 coefficient in Equation 12 implies that farmers also take into account the potential of saved effort when choosing plots for insurance.[35]

9 Conclusions

In contrast to the setup of a typical randomized experiment, the experiment in this paper involved a two-step procedure in which farmers made a choice in the first stage that determined randomization probabilities in the second stage. Chassang, Padró i Miquel and Snowberg (2012) studied a similar mechanism that they term *selective trials* in which agents in an experiment make probabilistic choices. In contrast to Chassang, Padró i Miquel and Snowberg (2012), where agents choose how much to pay for participation in a program (though elicitation of willingness-to-pay), the farmers in this experiment chose between alternative

[35] In the framework of the model, farmers prefer plots with high $A_j\psi_j(\hat{e}_j^0 - \hat{e}_j^1)$.

(free) treatments.[36] The experiments studied by Chassang, Padró i Miquel and Snowberg (2012) can in theory identify the full distribution of marginal treatment effects (MTE's)[37], including the degree of essential heterogeneity, while the experimental setup here only identifies essential heterogeneity (manifesting as selection on moral hazard) in a relative sense. This approach is nevertheless a new experimental setup that may be useful (and potentially more practical) in some settings.

The empirical results show that farmers can leverage a great deal of private information when engaging with the crop insurance provider. This private information includes land features, actions, and anticipated actions, giving rise to adverse selection, moral hazard, and selection on moral hazard. I find strong evidence for adverse selection in both the insurance for typhoons and floods and the insurance for pests and crop diseases. I also find that the pest and crop disease coverage leads to moral hazard and selection on moral hazard, and it provides (small) disincentives for investment. Interestingly, I find none of these moral hazard effects among the subsample of risk averse farmers suggesting that these effects may be limited among paying customers who would tend to be the more risk averse. However, this may not apply to customers in PCIC's portfolio who often carry insurance coverage through combined credit and insurance contracts, which may draw in the less risk averse.

For a well-functioning market (even if it includes some subsidies), the insurance contracts need to either separate the low- and high-risk types into different contracts or the low-risk types must be willing to enter into a pooling contract. The large differences in risk that are evident from the data make the latter difficult. This is particularly true since the contract is covering risk that is relatively routine (13.6% of insured plots get some payout) and often nowhere close to catastrophic (23% of payouts are for less than 33% total loss). Assuming that farmers are substantially risk averse, such a contract is less valuable (dollar-for-dollar) than one that exclusively covers catastrophic losses. Adjusting this contract towards covering only the catastrophic losses would reduce verification costs (per unit of premium) and may, through a lower price and greater coverage of events with high utility cost, improve demand. But, based on the empirical findings, this change in design is likely to result in even greater adverse selection and moral hazard problems.

To make progress on designing insurance products for small scale farmers it is important to find the right balance between basis risk and asymmetric information problems and at the

[36] Here I think of a farmer with two plots being given the choice between two treatments. In treatment A, the farmer receives insurance on plot 1 but not on plot 2 and in treatment B the farmer receives insurance on plot 2 but not on plot 1.

[37] In the recent literature the concept of the MTE was introduced and developed in Heckman and Vytlacil (2005). According to Heckman (2010), this concept was first introduced by Bjorklund and Moffitt (1987) and further developed in Heckman and Vytlacil (2007).

same time expand the frontier of what is possible (e.g., through better data that can reduce one or both of these). This paper has shown that there are very substantial asymmetric information problems with the crop insurance for rice in the Philippines and that efforts to redesign the program by focusing only on specific hazards (such as only typhoons or floods, or only pests and crop diseases), or on covering only catastrophic losses, would lead to similar or worse problems with asymmetric information. The results on catastrophic losses show that new products that combine index insurance with catastrophic coverage through traditional crop insurance are unlikely to work. The most promising path forward is likely improved data collection through technology.

Table 3: EMPIRICAL ESTIMATES OF ADVERSE SELECTION AND MORAL HAZARD

	Harvest loss (percent) due to:						
	All causes		Typhoons and floods		Pests and diseases		Payout (1000's pesos)
First-choice	4.58 * **	3.63 * **	2.45 * **	1.67	2.13 * **	1.96 * *	0.97 * *
	(0.92)	(1.32)	(0.82)	(1.17)	(0.67)	(0.92)	(0.39)
Insurance	1.06	0.18	−0.60	−1.33	1.66 * **	1.51*	
	(0.92)	(1.21)	(0.78)	(1.08)	(0.63)	(0.84)	
First-choice X Insurance		2.57		2.12		0.45	
		(2.38)		(2.10)		(1.82)	
Area (hectares, centered)	1.54	1.54	0.84	0.85	0.70	0.70	−0.84
	(1.54)	(1.54)	(1.12)	(1.12)	(1.22)	(1.22)	(0.59)
Farmer-season FE	Yes		Yes		Yes		Yes
Sample:	Excluding first choice plots of farmers in the choice group						Insured plots
Mean of non-first choice plots	22.2	22.2	15.0	15.0	7.3	7.3	1.4
Mean of non-insured plots	23.5	23.5	15.8	15.8	7.7	7.7	
Num FE's	696	696	696	696	696	696	493
Observations	1740	1740	1740	1740	1740	1740	1775

This table shows separate estimation adverse selection and moral hazard using estimation equation 5. In the first 6 columns I exclude first-choice plots of farmers in the choice group, while the last column includes only insured plots. Damages reported in the first six columns are based on self-reports from a follow-up survey, while payouts in the last column are based on administrative data. The identification of the selection coefficient in the last column is based on the 92 farmers (of the total of 493 farmers in the two treatment groups) who had both their first choice plot and at least one other plot insured. Standard errors are corrected for spatial dependence using the method developed by Conley (1999). Significance stars: * < 0.1; ** < 0.05; *** < 0.01.

Table 4: Asymmetric Information in Catastrophic Coverage

	Typhoons and floods		Pests and Crop Diseases	
	Damage > 66%	Damage > 10%	Damage > 33%	Damage > 10%
First-choice	0.024 ∗ ∗	0.029∗	0.029 ∗ ∗	0.044 ∗ ∗∗
	(0.0093)	(0.016)	(0.012)	(0.015)
Insurance	0.00011	−0.014	0.027 ∗ ∗	0.020
	(0.0091)	(0.016)	(0.011)	(0.015)
Area (hectares, centered)	0.0051	−0.013	0.033	0.018
	(0.011)	(0.028)	(0.022)	(0.026)
Farmer-season FE	Yes	Yes	Yes	Yes
Sample:	Excluding first-choice plots of farmers in the Choice group			
Mean of non-first choice plots	0.043	0.40	0.089	0.19
Mean of non-insured plots	0.050	0.41	0.094	0.20
Num FE's	696	696	696	696
Observations	1739	1739	1739	1739

This table shows separate estimation adverse selection and moral hazard using estimation equation 5. The outcome variables are indicators for damage above 66% and 10% for typhoon and floods (columns 1 and 2) and above 33% and 10% for pests and crop diseases (columns 3 and 4). Standard errors are corrected for spatial dependence using the method developed by Conley (1999). Significance stars: * < 0.1; ** < 0.05; *** < 0.01.

Table 5: Empirical Estimates of a Selection Model Based on Predicted Damages

	Outcome: Indicator for first choice plot	
	Odds-ratio [95% CI] (p-value)	Odds-ratio [95% CI] (p-value)
Predicted Total Damages:		
If Insured	$1.08***$	
	$[1.04, 1.12]$	
	0.00026	
If Not Insured		$1.08***$
		$[1.04, 1.13]$
		0.00031
Difference (Insured - Not Insured)		$1.07*$
		$[0.99, 1.14]$
		0.073
Land Arrangement (ref. = Sharecropping)		
Owner of plot	$2.09**$	$2.10**$
	$[1.06, 4.10]$	$[1.08, 4.07]$
Land under fixed rent	0.84	0.85
	$[0.42, 1.69]$	$[0.39, 1.83]$
Land mortaged in	0.61	0.62
	$[0.27, 1.40]$	$[0.27, 1.39]$
Land lent for free	1.53	1.56
	$[0.46, 5.12]$	$[0.45, 5.40]$
Other predictors of choice		
Plot size	$7.55***$	$7.48***$
	$[3.72, 15.3]$	$[3.71, 15.1]$
Number of farmer-seasons	484	484
Observations	1259	1259

Columns 1 and 3 present empirical estimates of Equation (10). The coefficients reported are odds ratios and in the brackets below I report 95% confidence intervals. I use the full sample for the choice models but predict damages only using the sample of farmers in the full randomization group (except that I exclude the data from the first season since the plot characteristics were not collected in that season). All models are calculated using a cluster bootstrap procedure (clustering at the farm-season level) with 500 repetitions of the prediction and choice estimation (to account for the fact that the predicted damages are computed values). Significance stars: * < 0.1; ** < 0.05; *** < 0.01.

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ONLINE APPENDIX

A Additional Results on the Model

This section includes additional model derivations and extensions that were not included in the main paper due to space limitations. First, I present the farmers problem and then derive the optimal effort. Next, I present the value function for insurance choice (but, again due to space constraints, the proof of optimal insurance choices are presented in the Online Appendix). Finally, I extend the model to include a productive investment input to understand possible interactions between moral hazard and fertilizer investments.

A.1 Farmers maximization problem

Given the uniform distribution for the share of harvest lost, S, we have: $E\left[S_j|e_j\right] = \frac{1}{2}\theta_j(1-e_j)$ and $Var\left[S_j|e_j\right] = \frac{1}{12}\theta_j^2(1-e_j)^2$. This implies that

$$E\left[\Pi|(\alpha,\mathbf{e})\right] = \sum_{j=1}^{N} A_j\left(1-\frac{1}{2}(1-\alpha_j L)\theta_j(1-e_j)\right) - C(\mathbf{e})$$

and $Var\left[\Pi|(\alpha,\mathbf{e})\right] = \frac{1}{12}\sum_{j=1}^{N} A_j^2(1-\alpha_j L)^2\theta_j^2(1-e_j)^2$. The farmers maximization problem is to choose one plot as her preferred plot for insurance and then choose effort level on each plot conditional on its insurance coverage:

$$\max_{\alpha,\mathbf{e}}\sum_{j=1}^{N}\left[A_j\left(1-\frac{1}{2}(1-\alpha_j L)\theta_j(1-e_j)\right) - \rho(1-\tau)\frac{1}{12}A_j^2(1-\alpha_j L)^2\theta_j^2(1-e_j)^2\right] - C(\mathbf{e})$$

A.2 Optimal Effort

Optimal effort given insurance coverage is given by the solution to:

$$\begin{aligned}\widehat{\mathbf{e}}(\alpha) = \arg\max_{\mathbf{e}}\sum_{j=1}^{N}[\ A_j\left(1-\frac{1}{2}(1-\alpha_j L)\theta_j(1-e_j)\right) \\ -\rho(1-\tau)\frac{1}{12}\sum_{j=1}^{N} A_j^2(1-\alpha_j L)^2\theta_j^2(1-e_j)^2\ ] - C(\mathbf{e})\end{aligned}$$

The first order condition for effort is

$$
\begin{aligned}
\frac{\partial C}{\partial e_j} &= A_j\left[\frac{(1-\alpha_j L)\theta_j}{2} - \rho(1-\tau)A_j(1-\alpha_j L)^2\theta_j^2\frac{-2(1-e_j)}{12}\right] \\
&= A_j(1-\alpha_j L)\theta_j\left[\frac{1}{2} + \rho(1-\tau)A_j(1-\alpha_j L)\theta_j\frac{1-e_j}{6}\right] \\
&= W_j\left[1+\rho(1-\tau)W_j\frac{2(1-e_j)}{3}\right] = 0
\end{aligned}
$$

where $W_j = A_j w_j$, and I define $w_j = \frac{1}{2}(1-\alpha_j L)\theta_j$ as the per-hectare harvest at risk on plot j (i.e., the expected monetary loss if no effort is applied).[38] This amount will be prominent in the calculations below and I use it as a convenient shorthand.

The first order condition for effort implies that:

$$
\begin{aligned}
& A_j\psi_j = W_j\left[1+\rho(1-\tau)W_j\frac{2(1-e_j)}{3}\right] \\
\Leftrightarrow \quad & \rho(1-\tau)W_j\frac{2(1-e_j)}{3} = \frac{A_j\psi_j}{W_j} - 1 \\
\Leftrightarrow \quad & 1-e_j = \frac{3A_j\psi_j}{2\rho(1-\tau)W_j^2} - \frac{3}{2\rho(1-\tau)W_j} \\
\Leftrightarrow \quad & e_j = 1 - \frac{3A_j\psi_j}{2\rho(1-\tau)W_j^2} + \frac{3}{2\rho(1-\tau)W_j} \\
\Leftrightarrow \quad & e_j = 1 - \frac{3}{2}\frac{\psi_j - w_j}{\rho(1-\tau)A_j w_j^2}
\end{aligned}
\tag{14}
$$

For an interior solution we must have $e_j \in (0,1)$. This implies for an interior solution we must have $e_j > 0 \Leftrightarrow \psi_j < w_j + \frac{2}{3}\rho(1-\tau)A_j^2 w_j^2$ and $e_j < 1 \Leftrightarrow w_j < \psi_j$. This implies that optimal effort is given by:

$$
\hat{e}_j(\alpha_j,\theta_j,\psi_j,A_j,\rho,\tau) = \begin{cases} 0 & \text{if } \psi_j \geq w_j + \frac{2}{3}\rho(1-\tau)A_j w_j^2 \\ 1-\frac{3}{2}\frac{\psi_j - w_j}{\rho(1-\tau)A_j w_j^2} & \text{if } w_j < \psi_j < w_j + \frac{2}{3}\rho(1-\tau)A_j w_j^2 \\ 1 & \text{if } \psi_j \leq w_j \end{cases}
\tag{15}
$$

Figure I.1 depicts this function for a given plot, both when it is insured and when it is not insured.

[38]The second order condition for a local maximum is $-\rho(1-\tau)\frac{W_j^2}{6} < 0$, which is always satisfied.

A.3 Value Function for Insurance Choice

Given the optimal effort $\hat{e}_j(\alpha_j, \theta_j, \psi_j, A_j, \rho, \tau)$, the utility output on plot j is:

$$\begin{aligned} u_j(\alpha_j, \theta_j, \psi_j, A_j, \rho) = A_j &- A_j w_j(1 - \hat{e}(\alpha_j, \psi_j, \rho, A_j, w_j)) \\ &- \frac{\rho(1-\tau)}{3} A_j^2 w_j^2 (1 - \hat{e}(\alpha_j, \psi_j, \rho, A_j, w_j))^2 \\ &- A_j \psi_j \hat{e}(\alpha_j, \psi_j, \rho, A_j, w_j) \end{aligned} \tag{16}$$

Therefore, the correct value function for insurance choice used by the fully sophisticated farmer is $V(\alpha) = \sum_{j=1}^{N} u_j(\alpha_j, \theta_j, \psi_j, A_j, \rho)$ and her maximization problem when choosing the plot to designate as first choice is $\max_\alpha V(\alpha)$ subject to $\alpha_j \in \{0, 1\}$ and $\sum_{j=1}^{N} \alpha_j = 1$. In contrast, the less sophisticated (partially myopic) farmer bases her insurance choice decision on plot specific utility that does not take into account the effect of insurance on effort – that is, she assumes an effort function $\hat{e}^{myopic}(\theta_j, \psi_j, A_j, \rho) = \hat{e}(0, \theta_j, \psi_j, A_j, \rho)$ and an associated utility (u_j^{myopic}) and value function (V^{myopic}), obtained by substituting $\hat{e}^{myopic}$ for $\hat{e}$ in the utility output (equation 16) and substituting u_j^{myopic} for u_j in the value function.

A.4 Extending the Model with Productive Investment

Farmers expend effort and resources not only to prevent damages but also to increase yield through other means. I now extend the model to allow for the use of a productive investment input, such as fertilizer. In this section α (insurance) is not a choice variable because the goal is to understand how effort and investment interact in response to exogenous insurance provision and to empirically test these implications using the randomized experiment. Output on a plot when no damages occur is now assumed to be $G(f_j)$ instead of 1, where G is increasing and concave and f_j is the amount of investment input applied to plot j. I assume the price of the investment input is p_f so that the cost function for investment is $F(\mathbf{f}) = p_f \sum_j^N f_j$. The farmer jointly determines the level of effort and investment across a portfolio of plots. The profit function is now defined as $\Pi(e, f) = \sum_j^N \{G(f_j)A_j(1 - S_j) + \alpha_j L S_j A_j\} - C(\mathbf{e}) - F(\mathbf{f})$. Using the properties of the exponential utility as before the farmers maximization problem becomes:

$$\begin{aligned} \max_{\mathbf{e},\mathbf{f}} \sum_j^N A_j &\left[G(f_j) - \frac{1}{2}(G(f_j) - \alpha_j L)\theta_j(1 - e_j) \right] \\ &- \rho(1-\tau)\frac{1}{12} A_j^2 (G(f_j) - \alpha_j L)^2 \theta_j^2 (1 - e_j)^2 - C(\mathbf{e}) - F(\mathbf{f}) \end{aligned} \tag{17}$$

Because of how the insurance contract is structured, insurance coverage does not affect the marginal expected return to the investment input except through changes in effort provision.[39] However, insurance coverage can affect investment through the joint determination of effort and investment. The insurance coverage incentivizes less effort to prevent damages which in turn makes additional productive investments (such as fertilizer) less cost effective and more risky. Under plausible assumptions, this model yields the prediction that insurance coverage reduces productive investment.[40]

B Additional Model Results

B.1 Comparative Statics for Effort

If the solution for effort is interior, the comparative statics are the following:

$$\begin{aligned}
\frac{\partial e}{\partial \theta_j} &= \frac{\partial e}{\partial W_j}\frac{\partial W_j}{\partial \theta_j} \\
&= \left[-(-2)\frac{3A_j\psi_j}{2\rho(1-\tau)W_j^2} - \frac{3}{2\rho(1-\tau)W_j^2}\right](\frac{1}{2}A_j(1-\alpha_j L)) \\
&= \frac{6A_j\psi_j - 3W_j}{2\rho(1-\tau)W_j^3}(\frac{1}{2}A_j(1-\alpha_j L)) > 0 \quad (\text{by } \textbf{??}) \frac{\partial e}{\partial \psi_j} = -\frac{3A_j}{2\rho(1-\tau)W_j^2} < 0 \\
\frac{\partial \hat{e}}{\partial A_j} &> 0 \\
\frac{\partial e}{\partial \rho(1-\tau)} &= \frac{3(A_j\psi_j - W_j)}{4\rho^2(1-\tau)^2W_j^2} > 0
\end{aligned}$$

That is:

[39] Insurance coverage does reduce the variance of returns and can therefore impact investment directly (i.e., not through incentives for less effort provision). Given farmers risk aversion, this direct effect provides incentives for more investment.

[40] To illustrate this prediction, first note that the first-order condition with respect to investment is $p_f = G'(f_j)\{A_j\left[1-\frac{1}{2}\theta(1-e)\right] - \frac{1}{6}\rho(1-\tau)A_j^2(G(f_j)-\alpha_j L)\theta_j^2(1-e_j)^2\}$. Now, taking the derivative of this equation with respect to effort, we have:

$$\frac{\partial^2 G}{\partial f^2}\frac{\partial f}{\partial e} = \frac{-p_f\{\overbrace{\frac{1}{2}\theta_j A_j}^{>0} - \frac{1}{12}\rho(1-\tau)\theta_j^2 A_j^2\left[\overbrace{2\frac{\partial G}{\partial f}\frac{\partial f}{\partial e}(1-e_j)^2}^{\text{assumed small}} - \overbrace{2(G(f)-\alpha_j L)2(1-e_j)}^{>0}\right]\}}{(A_j\left[1-\frac{1}{2}\theta_j(1-e_j)\right] - \frac{1}{6}\rho(1-\tau)A_j^2(G(f_j)-\alpha_j L)\theta_j^2(1-e_j)^2)^2} < 0$$

To obtain the final inequality I assume the first term in the bracket is small relative to the second term. This assumption seems reasonable since the first term is the product of two marginal effects (on G and f) whereas the second term includes the level of $G(f)-\alpha_j L$ and insurance coverage is far from complete. Given that G is assumed concave, we have $\frac{\partial f}{\partial e} > 0$; that is, reduced preventative effort reduces investment.

1. $\frac{\partial \hat{e}}{\partial \theta_j} > 0$ (effort is increasing in the inherent riskiness)

2. $\frac{\partial \hat{e}}{\partial \psi_j} < 0$ (effort is decreasing in cost of effort)

3. $\frac{\partial \hat{e}}{\partial A_j} > 0$ (effort is increasing in area)

4. $\frac{\partial \hat{e}}{\partial \rho} > 0$ (effort is increasing in risk aversion)

5. $\frac{\partial \hat{e}}{\partial \tau} < 0$ (effort is decreasing in informal risk sharing)[41]

These comparative statics also apply at the lower corner – that is, for the probability that effort is positive. More formally, if ψ follows a distribution F, we define $\bar{\psi}_j = \frac{3W_j + 2\rho(1-\tau)W_j^2}{3A_j}$ and $p_j = Prob(\hat{e}_j > 0) = Prob(\psi_j < \bar{\psi}_j) = F(\bar{\psi}_j)$, then $\frac{\partial p_j}{\partial \theta_j} > 0$, $\frac{\partial p_j}{\partial \rho(1-\tau)} > 0$ and $\frac{\partial p_j}{\partial A_j} > 0$. Then

$$\begin{aligned}
\frac{\partial p}{\partial w} &= \frac{\partial F}{\partial w} = F'(\bar{\psi})\frac{3 + 4\rho(1-\tau)W}{3A} > 0 \\
\frac{\partial p}{\partial \theta} &= F'(\bar{\psi})\frac{3 + 4\rho(1-\tau)W}{3A}\frac{1}{2}A(1-\alpha L) > 0 \\
\frac{\partial p}{\partial \rho(1-\tau)} &= F'(\bar{\psi})\frac{2W^2}{3A} > 0 \\
\frac{\partial p}{\partial A} &= F'(\bar{\psi})\frac{1}{6}\rho(1-\tau)\theta^2(1-\alpha L)^2 > 0
\end{aligned}$$

At the upper corner, the probability that $\hat{e}_j = 1$ is increasing in θ_j and w_j but unaffected by ρ or A_j. Then

$$\begin{aligned}
\frac{\partial q}{\partial w} &= F'(\hat{\psi}) > 0 \\
\frac{\partial q}{\partial \theta} &= F'(\hat{\psi})\frac{1}{2}A(1-\alpha L) > 0 \\
\frac{\partial q}{\partial \rho} &= 0 \\
\frac{\partial q}{\partial A} &= 0
\end{aligned}$$

B.2 Derivation of Optimal Insurance Choice for a Partially Myopic Farmer

In this section I show that the optimal insurance choice of a farmer that does not anticipate her endogenous effort response to insurance is to choose the plot that has the highest expected

[41] The model assumes that effort is hidden to the informal insurance network, otherwise there may be no effect here.

payout. I first define a loss function, Λ, that represents the total harvest losses net of insurance payouts and net of effort costs used to prevent damages. Define

$$\begin{aligned}\Lambda(\alpha,\theta,\psi,\mathbf{A},\rho(1-\tau)) = &\sum_{j=1}^{N} A_j w_j (1-\hat{e}(\alpha_j,\theta_j,\psi_j,A_j,\rho(1-\tau))) \\ &+ \frac{\rho(1-\tau)}{3} A_j^2 w_j^2 (1-\hat{e}(\alpha_j,\theta_j,\psi_j,A_j,\rho(1-\tau)))^2 \\ &+ A_j\psi_j(\hat{e}(\alpha_j,\theta_j,\psi_j,A_j,\rho(1-\tau))) \end{aligned} \tag{18}$$

With this definition, total profits are equal to potential harvest less total losses: $\Pi(\alpha,\theta,\psi,\mathbf{A},\rho(1-\tau)) = \sum_{j=1}^{N} A_j - \Lambda(\alpha,\theta,\psi,\mathbf{A},\rho(1-\tau))$. Since the first term is not impacted by the farmers' actions, she chooses insurance to minimize costs (effort and damages) from natural hazards:

$$\hat{\alpha} = \arg\min_{\alpha} \Lambda(\alpha,\psi_j,,\rho(1-\tau),\mathbf{A},\mathbf{w}) \tag{19}$$

Since the farmer does not take into account her anticipated moral hazard response to insurance then she chooses a plot for insurance assuming she will apply effort equal to $\hat{e}(0,\psi_j,\rho(1-\tau),A_j,w_j)$ on plot j (i.e., effort as if the plot will not be insured). Below I will use $\hat{e}_0^j$ as a shorthand for $\hat{e}(0,\psi_j,\rho(1-\tau),A_j,w_j)$. I define the function λ by $\lambda(x,y) = \frac{1}{2}xy + \frac{\rho(1-\tau)}{12}x^2y^2$. Then

$$\begin{aligned}\Lambda(\alpha,\theta,\psi,\mathbf{A},\rho(1-\tau)) &= \sum_{j=1}^{N} A_j \left\{ A_j w_j(1-\hat{e}_0^j) + \frac{\rho(1-\tau)}{3} A_j^2 w_j^2 (1-\hat{e}_0^j)^2 + A_j\psi_j\hat{e}_0^j \right\} \\ &\equiv \sum_{j=1}^{N} \lambda(A_j\theta_j(1-\hat{e}_0^j),(1-\alpha_j L)) - \sum_{j=1}^{N} A_j\psi_j\hat{e}_0^j \end{aligned}$$

Since $\sum_{j=1}^{N} A_j\psi_j\hat{e}_0^j$ is independent of the insurance choice the λ function will determine the plot chosen. Now consider two plots, h and l with $A_h\theta_h(1-\hat{e}_0^h) > A_l\theta_l(1-\hat{e}_0^l)$. I will show that plot h is chosen as first choice plot if this inequality holds for all other plots l in the portfolio. Let $\Lambda((\alpha_h = 1, \alpha_{-h} = 0))$ represent the total loss if plot h is insured but all other plots are not insured. Now the difference in total losses between choosing plot h and plot l

for insurance is

$$\begin{aligned}
&\Lambda((\alpha_h = 1, \alpha_{-h} = 0)) - \Lambda((\alpha_l = 1, \alpha_{-l} = 0)) \\
= \quad & \lambda(A_h\theta_h(1-\hat{e}_0^h), (1-L)) - \lambda(A_l\theta_l(1-\hat{e}_0^l), (1-L)) \\
&+ \lambda(A_l\theta_l(1-\hat{e}_0^l), 1) - \lambda(A_h\theta_h(1-\hat{e}_0^h), 1) \\
\equiv \quad & M(A_h\theta_h(1-\hat{e}_0^h))
\end{aligned} \tag{20}$$

where I define the function M relative to a given plot l. Now to show that plot h will be chosen I must show that $M(A_h\theta_h(1-\hat{e}_0^h) < 0$. Now we have

$$\begin{aligned}
\frac{\partial\lambda(A\theta(1-\hat{e}_0), (1-\alpha L))}{\partial A\theta(1-\hat{e}_0)} &= \frac{1}{4}(1-\alpha L) + \frac{\rho(1-\tau)}{6}A\theta(1-\hat{e}_0)(1-\alpha L)^2 > 0 \\
\frac{\partial\lambda(A\theta, (1-\alpha L))}{\partial(1-\alpha L)} &= \frac{1}{4}A\theta(1-\hat{e}_0) + \frac{\rho(1-\tau)}{6}(A\theta(1-\hat{e}_0))^2(1-\alpha L) > 0 \\
\frac{\partial^2\lambda(A\theta, (1-\alpha L))}{\partial A\theta\partial(1-\alpha L)} &= \frac{1}{4} + \frac{\rho(1-\tau)}{3}(A\theta(1-\hat{e}_0))(1-\alpha L) > 0
\end{aligned} \tag{21}$$

Given that $M(A_l\theta_l(1-\hat{e}_0)) = 0$ we have

$$\begin{aligned}
M(A_h\theta_h(1-\hat{e}_0^h)) &= M(A_h\theta_h(1-\hat{e}_0^h)) - M(A_l\theta_l(1-\hat{e}_0^l)) \\
&= \int_{A_l\theta_l(1-\hat{e}_0^l)}^{A_h\theta_h(1-\hat{e}_0^h)} \frac{\partial M(s)}{\partial A\theta(1-\hat{e}_0)} ds \\
&= \int_{A_l\theta_l(1-\hat{e}_0^l)}^{A_h\theta_h(1-\hat{e}_0^h)} \left(\frac{\partial\lambda(s, 1-L)}{\partial A\theta(1-\hat{e}_0)} - \frac{\partial\lambda(s, 1)}{\partial A\theta(1-\hat{e}_0)}\right) ds \\
&= -\int_{A_l\theta_l(1-\hat{e}_0^l)}^{A_h\theta_h(1-\hat{e}_0^h)} \left(\frac{\partial\lambda(s, 1)}{\partial A\theta(1-\hat{e}_0)} - \frac{\partial\lambda(s, 1-L)}{\partial A\theta(1-\hat{e}_0)}\right) ds \\
&= -\int_{A_l\theta_l(1-\hat{e}_0^l)}^{A_h\theta_h(1-\hat{e}_0^h)} \int_{1-L}^{1} \underbrace{\frac{\lambda(s, m)}{\partial s\partial m}}_{>0 \text{ (by 21)}} dmds \\
&< 0
\end{aligned}$$

Therefore farmers prefer the plot with the largest $A\theta(1-\hat{e}_0)$. That is, since expected damages per hectare on the plot when not insured are equal to $\frac{1}{2}\theta(1-\hat{e}_0)$ this implies that the farmer chooses the plot that has the highest expected payout (area times expected damages per hectare).

C Attrition

A total of 839 farmers were enrolled in any of the three experimental seasons (counting repeat enrollees multiple times).[42] Of those, 10 farmers fell out of the experiment before farmers were informed of their insurance status because of sickness, death, mistake in enrollment or (in four cases) because they were already insured by the company (see Table H.2 in the Appendix for the breakdown by season). These farmers are left out of the intent-to-treat sample. Of the remaining 829 farmers, 698 are in the final analysis sample. Of the 131 farmers outside of the sample, 87 dropped out and 44 participated through the end (and were surveyed) but were unable to give information about output or damages. These 87 farmers dropped out because they refused surveys (44); because of sickness, death or migration (14); because they did not plant that season (16); or for unknown reasons (13). Table H.2 gives a breakdown of the reasons for attrition for each season.

D Damage Measure Construction

Collecting a panel of plot-specific information can bring certain practical challenges, such as misunderstandings between the farmer and the surveyor about which plot is which and whether specific information refers to a plot or the whole farm. The survey team employed various measures to minimize this risk. This included collecting information, for each plot, on the farmers tilling neighboring plots, and then reminding the farmer in subsequent survey rounds of the neighbors to the plot being discussed. Nevertheless, it seems clear from the data that some errors were made. To limit the impact of these errors on the estimates, I defined damage ratio observations as missing in the main sample if they were either more than 10 SD above the mean damage or if the damage reported was more than three times the mean output in the sample. In both of these cases, the damage reported likely refers to the larger farm but was mistakenly assigned to a specific plot. One observation of pest and disease damage fits both criteria. In addition, five observations of pest and disease damage and six observations of typhoon and flood damage fit the second criteria.[43] Section E shows that the findings are robust with respect to including these outliers.

The way the damage data was collected, where farmers were asked about total damages

[42]I use the term 'farmer' for farmer-season observations. That is, a farmer in multiple seasons is treated here as a separate observation in each case.

[43]These exclusions affect the parameter estimates primarily through the one observation that fits both criteria. This observation is for an unusually small plot (0.15 hectares) that doesn't satisfy the normal eligibility criteria (requiring plots to be more than 0.25 hectares) but was included by exception early on in the study.

(over the cropping season) due to a specific cause rather than specifying damages for each 'damage event', also presents challenges in comparing damages with payouts. Among insured plots, the correlation of total damages and payouts per hectare is 0.51; for typhoon and flood damages versus payouts for typhoons and floods, it is 0.49; and for pest and crop diseases, 0.37. One issue is that a series of small-scale crop losses could add up to a substantial total loss over the course of the cropping season, but this type of damage would not be covered by the insurance contract and could partly explain these low correlations. We also do not know the specific timing of each loss event. Both issues prevent us from creating damage measures that should correlate more strongly with the actual payouts.[44]

E Robustness of Adverse Selection and Moral Hazard Results

In Tables H.4 and H.5, I investigate the robustness of the above evidence on adverse selection and moral hazard. I estimate an equation of the same form as 5, but (in even columns) add controls for plot characteristics. The characteristics included are an index of flooding risk and indicators for the plot being at high risk from rats, tungro (a crop disease) or strong winds.[45] I perform the estimation for three different outcome variables in two separate samples. The outcome variables are (1) the damage ratio (as before), (2) the damage ratio winsorized at the 97.5th percentile, and (3) the log of the damage ratio. The sample used in the top panels is the full sample in which, in contrast to the sample used for the main results, I do not exclude the outliers discussed in Section **??**. In the bottom panels of the two tables I restrict the earlier sample to plots that fall in the middle 95% of a per hectare counterfactual harvest distribution, defined as the value of harvest plus damages divided by the plot size. This approach is one way to home in on the sample of plots that are more likely to give accurate results since it excludes very marginal plots or plots that the farmer did not seriously attempt to farm (the bottom 2.5%) and plots for which the harvest and damage data together suggest that either one may be inaccurate, for example when a farmer responds to a question about a particular plot with figures for the whole farm (the top 2.5%).

Columns 1, 3 and 5 in the top panel of Table H.4 show very strong evidence for adverse selection even if these outliers are included. The same is true for pests and crop diseases

[44]There are also some errors or irregularities in the damage and payout data. In particular, we have 7 plots (out of 756 randomly insured plots) that have positive payout even though recorded total damages are less than 10%.

[45]These baseline characteristics were not collected in the small first-season experiments and are missing for some plots in the later two seasons. In those cases I replace the indicator values with zero and the flooding index value with the sample mean.

(see Columns 1, 3 and 5 of Table H.5), but including these outliers slightly reduces the adverse selection estimate. Interestingly, the even columns of these two tables show that the observable characteristics can account for almost all of the adverse selection based on typhoon and flood damage but essentially none for pest and crop disease damage. These observables are self-reported by the farmer and are generally not available to the insurance company. Some related data (such as whether the plot lies low relative to surroundings) could be collected, but as discussed earlier, that may be prohibitively expensive given the contract value for typical plot. The first row in the bottom panels of the two tables show that the adverse selection estimates are robust to the sample restriction used. The estimate for typhoons and floods is slightly lower, but for pests and crop diseases, the estimate is slightly larger.

The second line of the top panel of Table H.5 shows that, even with these extreme outliers included, the moral hazard estimates are statistically significant at the 10% level for both the damage ratio and the log of the damage ratio. If we look at the corresponding line for the second sample, the results are robust to this restriction and in fact somewhat more statistically significant. In each case, as we would expect given the randomization, the coefficient estimates are essentially unchanged by including plot-level covariates.

F Simulation of Tradeoff Between Plot Size and Risk

In this section I describe the simulations I did to study the tradeoff between plot size and risk that was inherent in the plot choice decisions of farmers in the experiments. In the simulation we focus on the simpler case in which farmers do not take their effort response to insurance into account in their plot selection. In this case, the farmer chooses plot j if it has the largest value of $A_j\theta_j$ (area times risk) among the plots in the portfolio. The simulation exercise is designed to answer the question: What difference in damages would we observe between the first-choice plot and other plots if farmers instead choose the most risky plot (the one with the largest θ_j)? I simulated a portfolio of plots, ranging from two to five plots, in which each plot consists of a pair (A_j, θ_j) that is drawn from a bivariate uniform distribution with correlation ρ (between A_j and θ_j). I then simulated per-hectare damages, D_j, by drawing from a distribution that is uniform from zero to θ_j. For each portfolio, I identify the plot with the largest $A_j\theta_j$ and compute the difference in damages between this plot and (the average for) the other plots, denoting this amount ΔD_j^1. Likewise, I identify the plot with the largest θ_j and compute the difference in damages in the same way to obtain ΔD_j^2. The results for two and three plots are reported in Table H.7.

The first column gives the correlation that is assumed between plot size and risk. The second and fifth column provide the average difference in damages (in the simulations) between first-choice plots and other plots if farmers choose the plot with the largest $A_j\theta_j$ (as we expect to be the case in the data) whereas Columns 3 and 6 give the average difference in damages between first-choice plots and other plots if the farmer always chooses the plot with the largest θ_j. Columns 4 and 7 give the ratio between the earlier two columns. This ratio represents the counterfactual damages (in the simulation) that we would have observed if farmers selected without regard for the plot size. In the data, farmers have 2.6 plots on average and the empirical correlation between the share of harvest lost to all causes and plot size is 0.05. Therefore, Rows 3 and 4 may be the most relevant. I find that $\frac{\Delta\bar{D}^2}{\Delta\bar{D}^1}$ goes from 1.377 for $\rho = 0.1$ and three plots to 1.562 for $\rho = 0$ and two plots. These results suggest that, if the insurance had been given in a way that did not reward choosing a larger plot (e.g., if all farmers got insurance on a specific acreage), then the adverse selection estimates reported here would be on the order of 38-56% larger. [46]

G Share of Adverse Selection Predicted by Baseline Characteristics

In Table H.8 I estimate equations of the form

$$D_{ij} = \beta_0 + \beta_1 C_{ij} + \beta_2 X_{ij} + \beta_3 X_{ij} 1(\text{dry season}) + \lambda_i + \eta_{ij}. \tag{22}$$

I only use seasons 2 and 3 for this estimation since the relevant baseline characteristics were not collected in the first season. The estimated selection effect in Column 2 is 30% lower than in Column 1, where β_2 and β_3 are constrained to zero suggesting the observables explain a significant part of the observed selection effect.

[46]The model and the simulations above assume no correlation in shocks between plots. In reality these shocks are positively correlated (particularly for typhoon damage), which might shift some farmers away from choosing the plot with the largest expected damages and towards simply selecting the largest plot to maximize the payout after large shocks, such as total harvest loss on all plots. This reality would suggest that the main adverse selection estimates are further biased downwards. However, to evaluate this bias I am limited by the fact that I do not have good measures of this correlation over time (since I only have three cropping seasons).

H Appendix Tables

Table H.1: Farmer level intent-to-treat sample

ITT Status	Season 1	Season 2	Season 3	Total
Informed: In ITT sample	107	279	443	829
Not informed because already insured	1	3	0	4
Sick/dead/moved before he/she was informed	0	2	0	2
Mistake in enrollment / Not eligible	0	1	3	4
Total	108	285	446	839

This table reports on the construction of the ITT sample (number of farmers in each cell). A few farmers were randomized but never informed of their randomization allocation and didn't receive insurance through the experiment.

Table H.2: Farmer level attrition in the experiment

Dropout Status	Season 1 CT	Season 1 TX	Season 2 CT	Season 2 TX	Season 3 CT	Season 3 TX	Total
Not dropped: in final analysis sample	24	62	61	150	94	307	698
Died/sick/moved	0	0	4	2	4	4	14
Refused	5	3	7	12	6	11	44
Did not plant this season	1	1	2	5	1	6	16
Could not give output on any plot	0	0	5	11	5	5	26
Could not give any data on damages	0	2	2	14	0	0	18
Unknown	5	4	2	2	0	0	13
Total	35	72	83	196	110	333	829
Comparison	p = 0.53		p = 0.92		p = 0.69		

This table reports attrition (number of farmers) by season and (farmer level) treatment status (CT = Control, TX = Treatment). The last row presents p-values from a Chi-square test of the difference in attrition rates across treatment and control groups (for each phase).

Table H.3: Plot-level attrition in the experiment

	Season 1		Season 2		Season 3		
Dropout Status	CT	TX	CT	TX	CT	TX	Total
In sample	63	70	188	184	402	403	1,310
Could not report output or damages	7	9	25	18	37	35	131
Is worker on this plot, not farmer	0	0	0	1	3	1	5
Other	0	0	5	5	0	0	10
Total	70	79	218	208	442	439	1,456
Comparison	p = 1.00		p = .89		p = .96		

This table reports attrition (number of plots) by season and plot-level treatment status for plots included in the plot randomization (that is, excluding the pure control group and excluding first choice plots of farmers in the choice group), excluding plots of farmers that dropped out completely. The last row presents p-values from a Chi-square test of the difference in attrition rates across treatment and control groups (for each phase).

Table H.4: Robustness of the Adverse Selection and Moral Hazard Estimates on Typhoon and Flood Damage

	Harvest losses due to typhoons and floods measured as:					
	Raw Proportion		Proportion Winsorized at top 2.5%		Log of the Proportion	
			Sample: Full			
First-choice	2.46 ∗ ∗∗	0.82	2.42 ∗ ∗∗	0.79	0.19 ∗ ∗∗	0.057
	(0.82)	(0.82)	(0.81)	(0.82)	(0.068)	(0.069)
Insurance	−0.53	−0.81	−0.58	−0.86	−0.054	−0.077
	(0.78)	(0.77)	(0.78)	(0.77)	(0.065)	(0.065)
Flooding index		5.00 ∗ ∗∗		4.98 ∗ ∗∗		0.35 ∗ ∗∗
		(0.69)		(0.69)		(0.051)
High risk from winds		2.47		2.44		−0.053
		(2.63)		(2.63)		(0.18)
High risk of rats		−3.57 ∗ ∗∗		−3.60 ∗ ∗∗		−0.32 ∗ ∗∗
		(1.29)		(1.28)		(0.11)
High risk of tungro		0.083		0.078		0.19
		(1.87)		(1.86)		(0.15)
Area (hectares, centered)	0.83	1.33	0.83	1.33	0.033	0.070
	(1.12)	(1.08)	(1.12)	(1.07)	(0.11)	(0.10)
Mean of control plots	14.9	14.9	14.9	14.9	1.7	1.7
Num FE's	697	697	697	697	697	697
Observations	1744	1744	1744	1744	1744	1744
	Sample: Omitting top and bottom 2.5% of the potential harvest distribution					
First-choice	2.01 ∗ ∗	0.43	2.00 ∗ ∗	0.43	0.16 ∗ ∗	0.027
	(0.84)	(0.83)	(0.83)	(0.83)	(0.069)	(0.070)
Insurance	−0.26	−0.53	−0.25	−0.53	−0.041	−0.063
	(0.81)	(0.79)	(0.80)	(0.79)	(0.067)	(0.067)
Flooding index		4.82 ∗ ∗∗		4.80 ∗ ∗∗		0.35 ∗ ∗∗
		(0.68)		(0.67)		(0.051)
High risk from winds		0.40		0.37		−0.14
		(2.16)		(2.15)		(0.17)
High risk of rats		−4.50 ∗ ∗∗		−4.48 ∗ ∗∗		−0.39 ∗ ∗∗
		(1.38)		(1.36)		(0.12)
High risk of tungro		−0.019		−0.053		0.19
		(1.87)		(1.86)		(0.16)
Area (hectares, centered)	1.29	1.75∗	1.28	1.74∗	0.100	0.13
	(1.10)	(1.04)	(1.09)	(1.04)	(0.11)	(0.10)
Mean of control plots	14.6	14.6	14.6	14.6	1.7	1.7
Num FE's	686	686	686	686	686	686
Observations	1659	1659	1659	1659	1659	1659

This table explores the robustness of the adverse selection and moral hazard findings on typhoon and flood damage. In this table, I use all available data, including the outliers discussed in Section **??**. The three outcome variables are (1) the raw damage ratio; (2) the damage ratio constructed by winsorizing the damages and harvest the 97.5th percentile before constructing the ratio; and (3) the inverse hyperbolic sine transformation of the damage ratio. The inverse hyperbolic sine transformation ($f(x) = log(x + \sqrt{(x^2+1)})$; see e.g., Burbidge, Magee and Robb (1988)) can be interpreted in a similar way as a log transformation but has the advantage of being defined and differentiable at zero. In the lower panel I exclude plots in the top and bottom 2.5% of the counterfactual harvest distribution (harvest plus total damages) per hectare. The regressions include farmer-season fixed effects. Standard errors are corrected for spatial dependence using the method developed by Conley (1999). Significance stars: * < 0.1; ** < 0.05; *** < 0.01.

Table H.5: Robustness of the Adverse Selection and Moral Hazard Estimates on Pest and Crop Disease Damage

	Harvest losses due to pests and crop diseases measured as:					
	Raw Proportion		Proportion Winsorized at top 2.5%		Log of the Proportion	
			Sample: Full			
First-choice	1.98 * **	1.98 * **	1.98 * **	1.99 * **	0.25 * **	0.27 * **
	(0.67)	(0.69)	(0.66)	(0.67)	(0.065)	(0.066)
Insurance	1.26*	1.24*	1.30 * *	1.29 * *	0.12*	0.12*
	(0.66)	(0.67)	(0.65)	(0.65)	(0.063)	(0.064)
Flooding index		0.15		0.10		−0.022
		(0.49)		(0.46)		(0.044)
High risk from winds		2.25		2.27		0.30*
		(1.44)		(1.45)		(0.17)
High risk of rats		0.47		0.49		0.13
		(1.08)		(1.03)		(0.099)
High risk of tungro		0.42		0.46		0.092
		(1.64)		(1.62)		(0.14)
Area (hectares, centered)	0.64	0.66	0.74	0.76	0.10	0.10
	(1.23)	(1.23)	(1.21)	(1.21)	(0.11)	(0.11)
Mean of control plots	7.5	7.5	7.3	7.3	1.0	1.0
Num FE's	697	697	697	697	697	697
Observations	1744	1744	1744	1744	1744	1744
		Sample: Omitting top and bottom 2.5% of the potential harvest distribution				
First-choice	2.13 * **	2.19 * **	2.07 * **	2.14 * **	0.26 * **	0.28 * **
	(0.67)	(0.69)	(0.66)	(0.67)	(0.067)	(0.068)
Insurance	1.40 * *	1.40 * *	1.41 * *	1.41 * *	0.14 * *	0.14 * *
	(0.68)	(0.68)	(0.66)	(0.66)	(0.065)	(0.066)
Flooding index		0.037		−0.032		−0.041
		(0.50)		(0.48)		(0.045)
High risk from winds		1.97		1.87		0.25
		(1.57)		(1.57)		(0.18)
High risk of rats		1.34		1.22		0.19*
		(1.07)		(1.02)		(0.100)
High risk of tungro		0.58		0.64		0.12
		(1.52)		(1.49)		(0.14)
Area (hectares, centered)	−0.10	−0.12	−0.029	−0.050	0.059	0.052
	(1.24)	(1.24)	(1.22)	(1.22)	(0.12)	(0.12)
Mean of control plots	7.5	7.5	7.4	7.4	1.0	1.0
Num FE's	686	686	686	686	686	686
Observations	1659	1659	1659	1659	1659	1659

This table explores the robustness of the adverse selection and moral hazard findings on pest and crop disease damage. In this table, I use all available data, including the outliers discussed in Section **??**. The three outcome variables are (1) the raw damage ratio; (2) the damage ratio constructed by winsorizing the damages and harvest the 97.5th percentile before constructing the ratio; and (3) the inverse hyperbolic sine transformation of the damage ratio. The inverse hyperbolic sine transformation ($f(x) = log(x + \sqrt{(x^2 + 1)})$; see e.g., Burbidge, Magee and Robb (1988)) can be interpreted in a similar way as a log transformation but has the advantage of being defined and differentiable at zero. In the lower panel I exclude plots in the top and bottom 2.5% of the counterfactual harvest distribution (harvest plus total damages) per hectare. The regressions include farmer-season fixed effects. Standard errors are corrected for spatial dependence using the method developed by Conley (1999). Significance stars: * < 0.1; ** < 0.05; *** < 0.01.

Table H.6: Average Damages by Risk Aversion

	Harvest Loss (percent) Due to:	
	Typhoons and floods	Pests and diseases
Risk averse	-0.36	$-2.80**$
	(1.99)	(1.17)
Constant	$15.8***$	$8.85***$
	(0.91)	(0.77)
Observations	1654	1654

This table reports estimates of a simple regression of damages, for typhoons and floods in Column 1 and pests and crop diseases in Column 2, on the risk aversion measure. Standard errors are clustered at the farm-season level.

Table H.7: Simulation Results

	Two plots			Three plots		
ρ	$\Delta\bar{D}^1$	$\Delta\bar{D}^2$	$\frac{\Delta\bar{D}^2}{\Delta\bar{D}^1}$	$\Delta\bar{D}^1$	$\Delta\bar{D}^2$	$\frac{\Delta\bar{D}^2}{\Delta\bar{D}^1}$
-0.2	0.093	0.166	1.776	0.113	0.189	1.776
-0.1	0.100	0.167	1.662	0.123	0.190	1.551
0.0	0.106	0.166	1.562	0.131	0.191	1.459
0.1	0.113	0.165	1.458	0.139	0.191	1.377
0.2	0.120	0.165	1.378	0.145	0.191	1.319

This table reports the simulation results. The first row gives the correlation that is assumed between plot size (A_j) and risk (θ_j). I performed 10,000 simulations in each case and $\Delta\bar{D}^k$ is the average of Δ^k over those simulations (for $k = 1, 2$).

Table H.8: Estimated Share of Adverse Selection Explained by Baseline Characteristics

	Loss (%) Due to: All causes			
	Eq. (1)		Eq. (2)	
	Estimate	(SE)	Estimate	(SE)
First-choice	4.03 * **	[1.24]	2.84 * **	[1.24]
Plot size	21.3 * **	[3.68]	21.5 * **	[3.58]
Season 2 X Flooding index			2.55 * **	[1.22]
Season 2 X Medium risk of rats			4.44*	[4.36]
Season 2 X High risk of rats			1.28	[3.38]
Season 2 X Medium risk of tungro			4.64 * **	[2.66]
Season 2 X High risk of tungro			3.56	[5.31]
Season 3 X Flooding index			2.95 * **	[1.20]
Season 3 X Medium risk of rats			−1.09	[3.19]
Season 3 X High risk of rats			−0.63	[3.45]
Season 3 X Medium risk of tungro			1.30	[2.76]
Season 3 X High risk of tungro			3.35	[4.38]
Constant	13.3 * **	[0.46]	11.6 * **	[2.32]
F-test All Risk Characteristics				p = 0.00
Mean of dependent variable for non-first choice plots	12.4		12.4	
Num FE's	483		483	
Observations	1259		1259	

The table only includes data from Season 2 and 3 since these baseline characteristics were not collected in Season 1. Significance stars: * < 0.1; ** < 0.05; *** < 0.01.

Table H.9: Estimation of Predicted Damages by Treatment Group

	Loss Due to All Causes	
	Estimate	(SE)
Season 2 X Flooding index	6.97	(2.37)
Season 2 X Medium risk of rats	−3.99	(5.41)
Season 2 X High risk of rats	−12.5	(5.58)
Season 2 X Medium risk of tungro	0.14	(4.39)
Season 2 X High risk of tungro	1.45	(8.71)
Season 3 X Flooding index	3.21	(2.09)
Season 3 X Medium risk of rats	0.94	(5.02)
Season 3 X High risk of rats	−0.30	(5.28)
Season 3 X Medium risk of tungro	−2.71	(4.35)
Season 3 X High risk of tungro	−0.70	(6.81)
Insurance X Season 2 X Flooding index	−2.61	(2.47)
Insurance X Season 2 X Medium risk of rats	6.70	(5.18)
Insurance X Season 2 X High risk of rats	9.99	(6.48)
Insurance X Season 2 X Medium risk of tungro	−4.15	(4.51)
Insurance X Season 2 X High risk of tungro	1.47	(9.54)
Insurance X Season 3 X Flooding index	0.59	(2.79)
Insurance X Season 3 X Medium risk of rats	1.40	(5.14)
Insurance X Season 3 X High risk of rats	2.20	(5.71)
Insurance X Season 3 X Medium risk of tungro	3.96	(4.59)
Insurance X Season 3 X High risk of tungro	1.47	(7.59)
Insurance	−4.86	(3.69)
Constant	20.2	(3.71)
Observations	1259	

This table reports coefficient estimates for a model that predicts damages based on plot characteristics and insurance status. The predicted values from this regression are used in the selection model reported in Table 5 (these are estimates for the sample used to estimate the selection models; the bootstrap procedure used to estimate those models re-estimates this prediction model for each bootstrap sample). The outcome variable is total damages divided by the sum of total damages and harvest (I use this outcome variable instead of the damage measures used before to avoid using plot area as a part of the prediction model). The plot characteristics used are described in Section 5. The standard errors in Column 2 are estimated using OLS (this is only an illustration; as mentioned before, the prediction model is re-estimated for each bootstrap sample to estimate the selection model).

I Appendix Figures

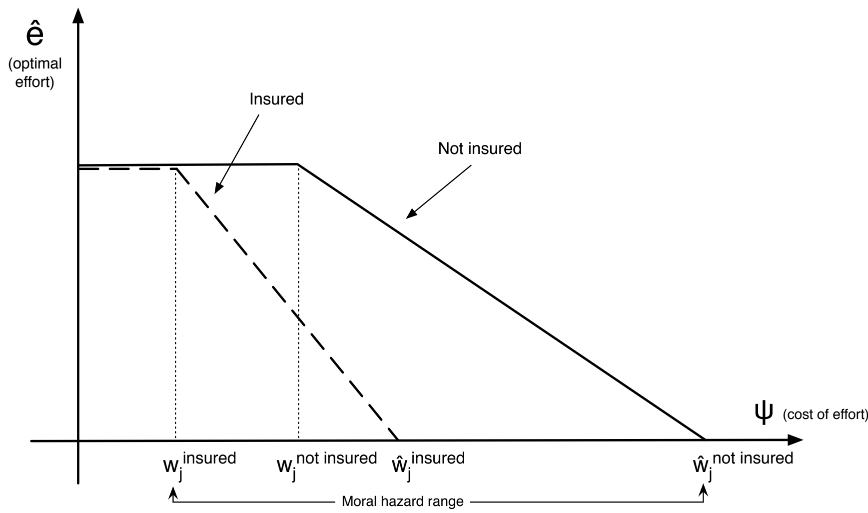

Figure I.1: Optimal effort, $\hat{e}_j$, as a function of the plot-specific cost of effort for insured and uninsured plots. Here, w_j^{insured} and $w_j^{\text{not insured}}$ denote w_j for insured and uninsured plots, respectively. Therefore, $w_j^{\text{insured}} = \frac{1}{2}\theta_j(1 - L)$ and $w_j^{\text{not insured}} = \frac{1}{2}\theta_j$. The upper boundaries are defined by $\hat{w}_j^{\text{insured}} = w_j^{\text{insured}} + \frac{2}{3}\rho A_j(w_j^{\text{insured}})^2$ and $\hat{w}_j^{\text{not insured}} = w_j^{\text{not insured}} + \frac{2}{3}\rho A_j(w_j^{\text{not insured}})^2$. The policy functions imply that, for plot j, effort is lower when the plot is insured if $w_j^{\text{insured}} < \psi < \hat{w}_j^{\text{not insured}}$, and otherwise equal.

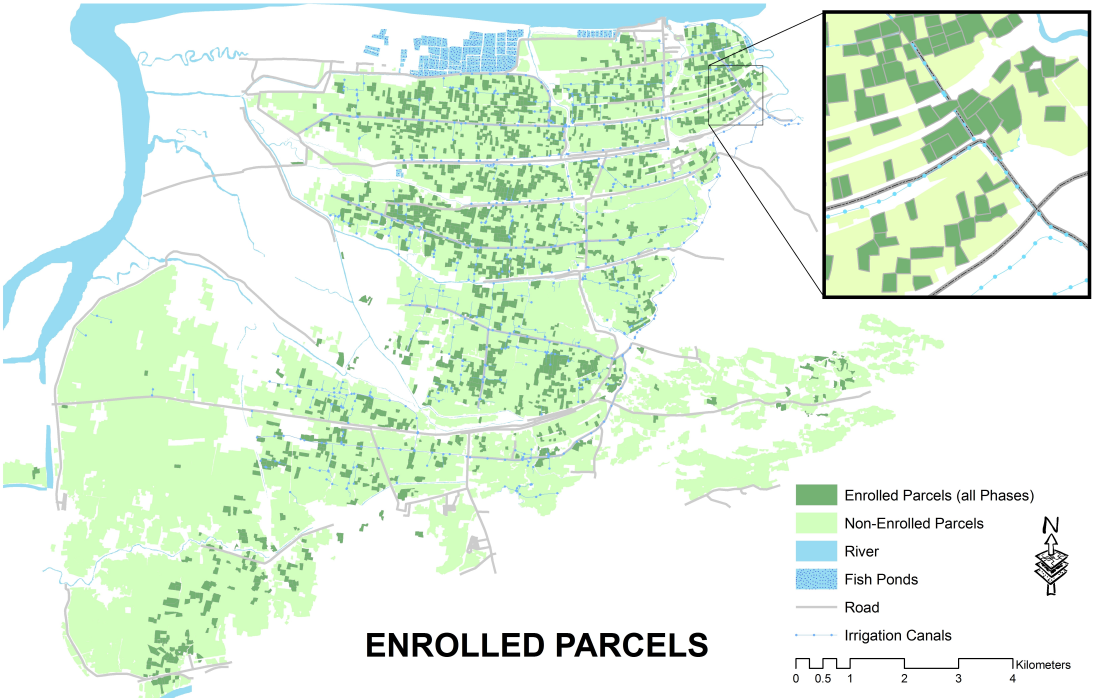

Figure I.2: This figure shows a map of the study area. Dark green plots are those that were a part of the study in at least one season while the light green plots are other rice plots.

J Insurance Contract Flier

The next two pages contain the flier that PCIC uses to market and explain the insurance contract.

GENERAL INFORMATION ON THE RICE CROP INSURANCE PROGRAM

OBJECT OF INSURANCE

The object of insurance shall be the standing rice crop planted on the farmland specified in the insurance application and which the assured farmer has an insurable interest on.

AMOUNT OF COVER

The insurance shall cover the cost of production inputs per Farm Plan and Budget, plus an additional amount of cover (at the option of the farmer) of up to a maximum of 20% hereof to cover portion of the value of the expected yield, subject to the following prescribed cover ceilings:

Inbred Varieties	
Irrigated/Rainfed	P41,000 per ha.
Seed Production	P50,000 per ha.
Hybrid Varieties	
Commercial Production (F1)	P50,000 per ha.
Seed Production (A x R)	P65,000 per ha.

TYPES OF INSURANCE COVER

Multi-Risk Cover - This is a comprehensive coverage against crop loss caused by natural disasters (i.e., typhoon, flood, drought, earthquake, and volcanic eruption) as well as pest infestation and plant diseases.

Natural Disaster Cover - This is a limited coverage against crop loss caused by natural disasters.

PERIOD OF COVER

The insurance coverage shall be from direct seeding or upon transplanting up to harvesting, provided that insurance coverage shall commence from the date of issuance of the Certificate of Insurance Cover (CIC) or, from the emergence of seed growth (coleoptiles), if direct seeded or upon transplanting, whichever is later.

INSURABLE RICE VARIETIES

All rice varieties accredited for production by the National Seed Industry Council (NSIC) are insurable.

PREMIUM RATE

Premium rate is variable per region, per season and per risk classification. This shall be shared by the farmer, lending institution and the government.

National Composite Rates and Premium Sharing (%)

Borrowing Farmers

	Multi-Risk Cover		
	Low Risk	Medium Risk	High Risk
Farmer	1.46	2.91	4.37
L.I.	2.00	2.00	2.00
Gov't.	5.90	5.90	5.90
Total	**9.36**	**10.81**	**12.27**
	Natural Disaster Cover		
	Low Risk	Medium Risk	High Risk
Farmer	1.12	2.23	3.35
L.I.	1.50	1.50	1.50
Gov't.	4.22	4.22	4.22
Total	**6.84**	**7.95**	**9.07**

Self-Financed Farmers

	Multi-Risk Cover		
	Low Risk	Medium Risk	High Risk
Farmer	3.46	4.91	6.37
Gov't.	5.90	5.90	5.90
Total	**9.36**	**10.81**	**12.27**
	Natural Disaster Cover		
	Low Risk	Medium Risk	High Risk
Farmer	2.62	3.73	4.85
Gov't.	4.22	4.22	4.22
Total	**6.84**	**7.95**	**9.07**

COVERED RISKS

- Natural disasters including typhoons, floods, drought, earthquakes, and volcanic eruptions.
- Plant diseases, e.g., tungro, rice blast/neck rot, grassy stunt, bacterial leaf blight and sheath blight.
- Pest infestation by any of the following major pests: rats, locusts, armyworms/cutworms, stemborer, black bugs and brown planthopper/hopperburn.

EXCLUDED RISKS

Losses arising from:

- Fire from whatever cause;
- Theft and robbery, pillage, sequestration, strikes or other commotion, war, invasion, acts of foreign enemies, hostilities (with or without declaration of war), civil war, rebellion, revolution, insurrection, acts of terrorism, military or usurped power or radio-active contamination whether controlled or uncontrolled;
- Any measure resorted by the government in the larger interest of the public;
- Avoidable risk emanating from or due to neglect of the assured/non-compliance with the accepted farm management practices by the assured or person authorized by him to work and care for the insured crop;
- Strong winds and heavy rains not induced by typhoon; and
- Any cause or risk not specified in the covered risks;
- Unintentional acts of persons, natural or judicial, that may cause damage to the insured crop; and
- Losses arising from failure to comply with the eligibility requirments.

Losses occurring:

- Prior to the effectivity of insurance;
- Prior to seed growth (coleoptile);
- Beyond the scheduled date of harverst, unless harvesting could not be undertaken on such scheduled dates due to adverse weather conditions as certified to by the production technician/municipal agricultural officer or death of the insured and the the subject loss occurs within five (5) days after the scheduled date of harvest.

FARMER/FARMER ORGANIZATION ELIGIBILITY

- Any borrowing farmer or group of farmers who obtains production loans from any lending institution participating in the government-supervised rice production program and GOCCs/GFIs/NGOs/DILG-LGUs-sponsored credit programs.
- Any self-financed farmer/farmer organization (FO)/ people's organization (PO) or group of farmers who agrees to place himself/themselves under the technical supervision of PCIC-accredited agricultural production technician.
- Any Farmer Organization (FO) or People's Organization (PO) or group of farmers duly qualified under the Government Corporation Insurance System (GCIS).

FARM ELIGIBILITY

- The farm must not be part of a riverbed, lakebed, marshland, shoreline or riverbank;
- The farm must have an effective irrigation and drainage systems. Rainfed areas are eligible farms during wet cropping season subject to planting cut-off date;
- The farm must be accessible to regular means of transportation;
- The farm must be suitable for production purposes in accordance with the recommended Package of Technology (POT), e.g., right zinc content; and
- Farm location must have generally stable peace and order condition and not hazardous to health.

DOCUMENTS REQUIRED IN APPLYING FOR COVER

Individual Borrowing Farmer

- Application for Production Loan (APL) which also serves as application for crop insurance.
- Farm Plan and Budget (FPB) - showing schedule of farm activities, e.g.,date of planting and harvest, etc.
- Location Sketch Plan (LSP)/Control Map (CM)- showing landmarks and names of adjoining lot owners.

Farmers Borrowing as a Group

- List of Borrowers (LOB)- containing the names and addresses of the borrowers, the farm area, location, planting schedules, variety, amount of loan and signatures of borrowers.
- Standard Farm Plan and Budget (SFPB)
- Control Map (CM)

Self-financed Farmer

- Application for Crop Insurance (ACI)
- Farm Plan and Budget (FPB)
- Location Sketch Plan (LSP)/Control Map (CM)

WHERE TO FILE APPLICATION FOR COVERAGE

- Lending institution where farmers obtained their production loans.
- PCIC Regional Offices/PCIC authorized underwriting agents.

WHEN TO FILE APPLICATION FOR COVERAGE

Any day before the date of planting up to fifteen (15) calendar days after planting.

NOTICE OF LOSS

In the event of loss arising from risks insured against, a written Notice of Loss (NL) shall be sent to the PCIC Regional Office within ten (10) calendar days from occurrence of loss and before the scheduled date of harvest. In cases where the cause of loss is due to pest infestation, disease or drought and where the effect of damage is gradual or the full extent thereof is not immediately determinable, the NL shall be filed upon discovery of loss. In no case shall this be later than twenty (20) calendar days before the scheduled date of harvest. The NL shall at least contain the following information: name of the assured farmer, CIC number, lot number, time of occurrence of loss, stage of cultivation, nature, cause and extent of loss.

CLAIM FOR INDEMNITY

The Claim for Indemnity (PCIC Indemnity Form) shall be filed by the assured farmer or any immediate member of his family with the concerned PCIC Regional Office within forty five (45) calendar days from occurrence of loss.

ADJUSTMENT AND SETTLEMENT OF CLAIM

Verification and Loss Assessment

A team of adjusters composed of two (2) members, one from PCIC and the other from either the DA/DILG or DAR or NIA or concerned LI, shall verify the claim.

Loss Category:

- Total loss - if loss is 90% and above.
- Partial loss - if loss is more than 10% and below 90%
- No loss - if loss is 10% or less.

Amount of Indemnity

The amount of indemnity shall be based on the ff:

- Stage of cultivation at time of loss.
- Actual CPI (per FPB) already applied at time of loss.
- Percentage of yield loss.

Settlement of Claim

A claim shall be settled as expeditiously as possible but not later than sixty (60) calendar days from submission by the affected farmers of complete claims documents to PCIC RO. A claim not acted upon 60 calendar days shall be considered approved.

NO-CLAIM BENEFIT

The assured is entitled to a no-claim benefit of ten percent (10%) of his net premium paid if he/she has not filed any claim during the immediately preceding three (3) insured crop seasons not subject of any claim.

DEATH BENEFIT

This is a built-in death benefit component of the insurance package for rice crop equivalent to P10,000 per assured farmer who may suffer death within the term of coverage; provided said farmer is not more than 75 years of age at the inception of insurance.

CROP INSURANCE FOR RICE

General Information on the Rice Crop Insurance Program

DEPARTMENT OF AGRICULTURE
PHILIPPINE CROP INSURANCE CORPORATION

"Sa Paglaban sa Kahirapan at Gutom, Crop Insurance, Katulong sa Pagbangon."

7th Floor, Building A, NIA Complex, EDSA, Diliman, Quezon City, Philippines
TeleFax (02) 441-1324
Email rmg@pcic.gov.ph