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The Impact of Formal Insurance Provision on Farmer Behavior: Evidence from Rural Zambia

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The Impact of Formal Insurance Provision on Farmer Behavior: Evidence from Rural Zambia*

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Abstract

This study presents empirical evidence of changes in farmer behavior after offering them weather index insurance contracts. To quantify the impacts of insurance on agricultural decision-making, this study makes use of the random allocation of free insurance to small-scale farmers in rural Zambia, while endogenous insurance demands are also investigated. Our empirical results show that the provision of insurance leads farmers to sow maize seeds earlier—a practice known to increase maize yield, but which is riskier in terms of rainfall variability. In addition, it is found that insured farmers enlarge the maize field size and use more fertilizer; that is, the provision of insurance encourages farmers to invest in maize production in a risky environment. We also report suggestive but interesting evidence that weather index insurance could substitute for small-livestock holdings, a conventional self-insurance tool used to mitigate income variation.

Key words: agriculture, risk, weather insurance, underinvestment, Africa
JEL Classifications: C93, D24, G22, O12, O13, O16, Q12, Q14

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1. Introduction

Maize is a major staple food produced in many parts of Sub-Saharan Africa, but its average yield in Sub-Saharan Africa is quite low, even compared to that in countries in other tropical rain-fed environments—1.4 tonnes/ha in Sub-Saharan Africa versus 3.8 tonnes/ha in Brazil and 3.9 tonnes/ha in Thailand, for example (Smale, Byerlee, and Jayne 2011). Therefore, enhancements in maize yield constitute an important policy objective among Sub-Saharan African countries. There are many reasons for the yield gap, but insufficient use of modern inputs—such as improved varieties and chemical fertilizer—has been frequently highlighted, and high production risk is considered one of the causes of low investment. In fact, the coefficient of variation of maize production in Sub-Saharan Africa is extremely high (Smale, Byerlee, and Jayne 2011). Since rainfall variability is responsible for maize production variability in rain-fed conditions, it is difficult to reduce the variability itself, except through the costly construction of irrigation facilities. This study considers the role of weather insurance and investigates its effect on investments in maize production in order to increase yield.

Given the low availability of irrigation schemes and farmers' poor access to weather-related information, weather shocks could constitute the most convincing explanation for high fluctuations in maize yields in Sub-Saharan Africa across years. In the absence of well-functioning insurance and credit markets, fluctuations in both weather patterns and consequent crop prices translate into the income shocks that agricultural households within the region face. Previous research has found that households utilize informal mechanisms to mitigate damages that stem from economic shocks, in order to stabilize their consumption. Examples include informal risk-sharing within a village as well as across areas, the selling of assets, and increasing labor supply after the shocks, all of which are typical examples of so-called *ex post* risk-coping strategies (Alderman and Paxson 1992). However, it is difficult to completely offset losses that stem from weather-related shocks through such *ex post* risk coping strategies, as they affect everyone in their local environment simultaneously. As a result, uninsured consumption fluctuations remain. Since variations in consumption itself cause welfare loss among risk-averse farmers, they have a strong incentive to stabilize income streams in advance by hedging income risk. Such farmer behavior geared toward reducing income variation comprises *ex ante* risk management strategies, or income smoothing (Morduch 1995). Income-smoothing activities used to mitigate production risk within the cropping system include operating multiple plots/crops, spatially scattering plots, and adopting conservative agricultural production techniques, such as the use of traditional seed varieties. Another important *ex ante* risk management strategy could involve precautionary savings. In general, agricultural households keep livestock as a way of storing wealth for precautionary purposes (Fafchamps, Udry, and Czukas 1998; Carter and Lybbert 2012).

The key observation here is that by undertaking such risk-mitigation activities, agricultural households could miss opportunities to invest in profitable agricultural technologies.[1] A few studies

[1] For instance, McIntosh, Sarris, and Papadopoulos (2013) estimate the marginal product of fertilizer in Ethiopia and find it to cost about 4,500 birr/ha—4.5 times larger than its average market price. Apparently, Ethiopian farmers could increase their expected agricultural profits by increasing the amounts of fertilizer applied. This seemingly inefficient behavior could be considered a typical

report direct empirical evidence regarding efficiency losses due to the effect of existing income risk on production technology choices. For instance, Rosenzweig and Binswanger (1993) find that in rainfall-variable environments, agricultural households tend to choose household-asset portfolios that are less sensitive to rainfall variation and thus less profitable. In addition, they calculate the quantitative impacts of income smoothing on profits and report that the efficiency loss associated with risk mitigation is higher among the poor. Zimmerman and Carter (2003) theoretically investigate the effect of uninsured risks on portfolio decisions and characterize optimal portfolio strategies, which vary with initial wealth level. Dercon (1996) finds that a store of liquid wealth in the form of livestock—a proxy for a household's available consumption security—is associated with a household's crop portfolio in Western Tanzania; this suggests that a household's *ex ante* responses to income risk depend on its ability to smooth consumption. Moreover, Kurosaki and Fafchamps (2002) structurally estimate how the crop choices of farmers in Pakistan are affected by price and yield risks. All in all, uninsured income risks—specifically weather risks in agricultural settings—hinder farmers from investing in more profitable agricultural activities. Thus, engagement in risk-mitigation activities, especially through agricultural production decisions, is a causal factor that helps explain the stagnant agricultural productivity that rural farmers in Sub-Saharan African countries encounter.

Lessons from the literature suggest that to provide farmers with a disincentive to engage in income smoothing and thus enhance agricultural yields, it is necessary to isolate them from risk constraints through policy intervention. In this line, offering weather index insurance to uninsured farmers would be a desirable and promising policy.[2] Insurance payout in weather index insurance is based on a publicly observable and objective weather index, such as rainfall and temperature, that highly correlates with agricultural outputs. This feature of weather index insurance contracts substantially reduces transaction costs and mediates moral hazard problems, both of which are otherwise main impediments to the diffusion of crop insurance that requires costly verification. In addition, unlike food aid in times of emergency, prompt provisions of insurance payouts can be facilitated once reference weather index information is revealed. Weather index insurance has two potential roles in enhancing household welfare. The first role is to work as a safety net by immediately compensating for crop loss due to weather failure, thus enabling farmers to stabilize their household incomes. Its second but more fascinating role is to push insured farmers to shift into a risky but more profitable agricultural production mode, thus potentially fostering agricultural profits as well as crop productivity. Quantifying the latter effects and understanding the mechanisms that work behind the scene is essential to fully evaluating the effectiveness of weather index

example of income smoothing. Another example of a risk-hedging activity would be diversifying the sowing date. Delayed seeding after the onset of rainfall often leads to significant yield losses. For example, Fakorede (1985) reports from agricultural experiments in Nigeria that maize yield could decrease by 30–38 kg/ha for every day by which sowing is delayed after the first planting.

[2] For an excellent review, see Carter (2012) and Miranda and Farrin (2012).

insurance and comparing it to other formal insurance schemes from a cost–benefit analysis viewpoint.[3]

In this study, we use detailed data from a field experiment in rural Zambia. Zambia is a typical maize-producing country in Sub-Saharan Africa; its average maize yield is low (2,285 kg/ha in 2004–2013) and the coefficient variation is much higher (0.147) than that of the world average (0.042) for the 2004–2013 period (FAO 2014). We empirically measure the impacts of weather index insurance on several dimensions of production-related decision-making by introducing a weather index insurance contract to local small-scale farmers who face substantial rainfall risk. The contract—the indexes of which are based on rainfall amounts observed in the first three months of the rainy season (December–February) at a local weather station—identifies both “drought” and “flood” conditions.[4] To compensate mainly for input losses due to frequent rainfall failure at the early stage of the agricultural season, we have set a high premium rate (33%) and a reasonably low premium (approximately USD1 per unit) for local farmers. In addition to actual insurance sales, free insurance contracts were randomly allocated to the survey households to generate purely exogenous variations in insurance payout. Despite the high premium rate and low premium, median farmers have enough insurance to purchase seed again in cases of rainfall failure at the onset of the rainy season. By exploiting exogenous variations in endogenous insurance demand as well as random variation in insurance payout, we test whether insured farmers invest in profitable agricultural technologies.

It is well known that in an ideal world with a complete insurance market, farmer’s production-related decision-making would be independent of household preferences that drive consumption-related decision-making. Thus, once a farmer is fully insured, each farmer would simply behave as a profit maximizer to maximize the presented discounted value of the profits generated by each agricultural input. This also means that farmers would cease to invest in income-smoothing activities in order to pre-emptively hedge income variations. However, imperfections in insurance markets can create fundamental nonseparabilities between consumption and production choices. Households with constrained access to insurance markets may choose to invest less in their farms than they would under perfect markets. Under such circumstances, if insurance markets are not complete and uninsured income risks constitute a binding constraint, the provision of insurance increases agricultural investments in risky inputs (e.g., the adoption of modern seed varieties and the application of fertilizer) and decreases those in risk-hedging inputs (e.g.,

[3] For instance, Gehrke (2014) discusses the employment guarantee of the National Rural Employment Guarantee Scheme (NREGS) in India, stating that it is an insurance mechanism for rural households. In fact, she finds that the scheme led farmers to adopt riskier crop choices after the program started.

[4] Onset risk—which is uncertainty related to the onset of the rainy season—might be more salient than rainfall risk, which is uncertainty related to annual rainfall. Takeshima (2012) analyzes the effects of onset risk, and he shows that investments in draft animals are more likely to be seen in high-onset-risk areas of rural Nigeria; this suggests that such investments might be underpinned by risk-mitigation motives, because draft animals significantly save labor demand, which is in turn highly associated with uncertain onset timing, at the beginning of the rainy season. The weather index insurance that this study considers takes into account onset risks by utilizing rainfall amounts in the month during the planting stage (December), though the reference index does not rely on delayed dates of onset. We investigate whether the weather index insurance contracts also mitigate onset risks as well as broader rainfall risks, by focusing on a farmer’s choice of sowing dates. The index insurance studied in Mobarak and Rosenzweig (2012) was meant to more directly indemnify agricultural losses due to delayed rainfall in monsoon season in India.

moisture conservation measures and investments in irrigation) on plots. These intuitive explanations are theoretically formalized in Karlan et al. (2014) with a simple two-period model in the two world states. A similar model is also found in Gehrke (2014). These theoretical predictions vis-à-vis the impacts of insurance on farmer behavior motivate the empirical examinations within this study.

Our empirical results show that insured farmers significantly expand maize fields in terms of operation size, along with increases in fertilizer application and family labor inputs; these findings are consistent with the theoretical prediction. Especially, we observe that family labor inputs greatly increase at the intensive margin. On the other hand, intensive margins of fertilizer application per plot do not respond to the provision of formal insurance. We also find that insured median farmers sow maize seeds about five days earlier than control farmers; this seemingly small change in the production plan would have significant impacts on maize yields, because the timing of sowing is a crucial determinant of maize productivity. In fact, experimental results from a controlled agricultural trial in the same study site show that delaying sowing by 10–20 days can reduce maize yields by 19%—about 125 kg/ha, on average—compared to those from a control plot (Shimono et al. 2012). Thus, the provision of weather index insurance encourages farmers to adopt risky but profitable agricultural inputs and shift production modes, thus enabling them to achieve higher yields. Moreover, the favorable impacts of the insurance provisions suggest that capital constraints are less tight than what we typically assume. To support this view, we report suggestive evidence that to source the money for agricultural inputs, insured farmers reduce small-livestock holdings—a conventional self-insurance tool used to mitigate income variations.

Karlan et al. (2014) is a notable complementary study, as it pertains to the provision of rainfall insurance to agricultural farmers in rural Ghana. However, the current study differs from Karlan et al. (2014) in the following two ways. The first difference is in the expected main role of the insurance contract. In the index insurance contract studied herein, insurance payouts are meant to compensate for agricultural input costs when frequent rainfall failure happens, specifically at the beginning of the agricultural season; in Karlan et al. (2014), however, they are meant to remediate the loss of an entire crop. For our purposes, we have set a high premium rate and a low premium. This sort of insurance scheme is in high demand—especially in rural Sub-Saharan Africa, where rainfall failure frequently happens and local farmers find it difficult to immediately source the necessary funds to reinvest in inputs once rainfall fails. Our striking empirical results suggest that farmers can respond to even small insurance levels, and that their behavioral changes on account of insurance provision work sufficiently to significantly increase their expected profits.[5] Since low demand for index insurance, as reported in the literature, might have stemmed from low premium rates and/or high premiums in a typical contract, this study instead proposes an alternative and promising direction by which to enhance the effectiveness of weather index insurance in developing countries.

[5] The same result might be obtained through the use of microcredit. In fact, Fink, Jack and Masiye (2015) use experimental data from a different region in Zambia (Chipata District) and show that small amounts of credit equal to ZMW200 (=USD40) made available during the lean season lead to higher agricultural productivity.

Second, this study conducts regression analysis at both the plot and household levels, and this allows us to investigate the effect of weather index insurance on changes of investment in agricultural inputs at both extensive and intensive margins, controlling for plot characteristics. We show that the insurance's effects on household *ex-ante* behavior at the intensive margin vary with the type of investment. Our findings from plot-level analysis provide unique insights and informative implications, as conventional household-level datasets used in the literature—such as Karlan et al. (2014) and Cole, Giné and Vickery (2014)—cannot decompose changes in the amounts of agricultural inputs into those related to land expansion and those related to intensification.

This study also explores the relationship between formal insurance provision and existing self-insurance mechanisms by focusing on small-livestock savings. Though this important empirical question has been raised from early on (Morduch 2006), little attempt has been made to answer it.[6] To help fill the related knowledge gap, we investigate small-livestock transactions following the provision of an insurance contract, as well as the impacts of small-livestock holdings on insurance demands. The following three aspects need to be considered. First, small-livestock holdings can be considered risk-hedging investments, as they are a low-risk alternative available at the cost of relatively low returns. Thus, once formal insurance is introduced, small-livestock savings would decrease similar to agricultural safer inputs. Second, whether informal self-insurance is a complement to or a substitute for formal index insurance depends on both the relative costs and the benefits between the two mechanisms. Especially, the nature of the relationship between small-livestock savings and weather index insurance would depend on what kind of shocks could be indemnified by dissaving small livestock, given basis risk in index insurance (Mobarak and Rosenzweig 2012). Third, to test the possibility of the complementarity between informal risk-sharing and insurance demand, it does not suffice to investigate the association between livestock savings and insurance demand. To fully determine the relationship, we also need to investigate farmer's adjustments to small-livestock savings *after* being insured. Our empirical results provide suggestive but interesting evidence of the substitutability between existing self-insurance and newly introduced formal insurance, although the estimated ratio of substitution between them is not found to be very high. We propose the interpretation that observed small-livestock sales by insured farmers indicate the sourcing of cash used to purchase profitable agricultural inputs.

[6] A few previous studies have shed light on the relationship with existing informal risk-sharing. Dercon et al. (2014) theoretically show that under the presence of basis risk (i.e., the potential mismatch between actual losses and insured losses), existing risk-sharing may crowd-in index insurance, as within-group risk-sharing can complement index insurance. Mobarak and Rosenzweig (2012) also discuss the possibility of the complementarity between informal risk-sharing and insurance demand when there is basis risk—although in their theory, the sign of the direction in their relation cannot be determined *ex ante*. Using field experiments in India, in which index insurance for the delayed onset of the monsoon was sold, they also empirically investigate how caste-based informal insurance affects insurance demand; they did so by examining a network's ability to indemnify losses, based on household survey data collected prior to the experiment. Their empirical findings suggest that informal insurance can be both a complement to and a substitute for formal index insurance, depending on the type of informal insurance arrangement made: while caste-network households that already indemnify against aggregate risk show less demand for the insurance product, the negative effect of basis risk is weakened for households in caste networks that indemnify idiosyncratic loss. On the other hand, Sakurai and Reardon (1997) showed that a hypothetical rainfall index insurance would reduce household's livestock holdings, an important self-insurance mechanism, in Burkina Faso. However, to the best of our knowledge, few studies have examined the relationship between formal insurance and existing self-insurance.

This paper is organized as follows. The following section describes the data we use. Section 3 presents the descriptive analysis of the demand for introduced weather index insurance. Section 4 discusses the empirical methodologies by which to estimate the causal impact of insurance on farmer behavior. Estimation results are discussed in Section 5, and robustness checks are presented in Section 6. Section 7 concludes.

2. Data

2.1. Study area

This study uses data from Southern Province, Zambia. Zambia is situated in the semi-arid tropics, where people's livelihoods depend mainly on rain-fed agriculture. Climatic variation, especially with regard to rainfall, is a substantial covariate risk that threatens the subsistence of small-scale farmers. In particular, Southern Province is known to be the most drought-prone area in the country; however, most of the local farmers do not have access to irrigation, and thus their agricultural practices are completely rain-fed. The main agricultural season coincides with the rainy season (November–April). During the season, farmers grow maize (the staple food in Zambia), cotton, sweet potatoes, and various vegetables. In the dry season (May–October), their agricultural activities are limited.

In Southern Province, three locations alongside Lake Kariba were selected for the household survey.[7] The three locations are a lower flat lake-side area (Site A), a middle escarpment area (Site B), and an upper terrace on the Zambian plateau (Site C). Although there are geographical differences among these three, maize farming is dominant in each of them. We selected four villages from Site A, three villages from Site B, and two villages from Site C. These nine villages, all of which are within a 15-km radius, are relatively close to each other. Nevertheless, rainfall amounts often differ from one village to another, due to geographical differences within such a small area —particularly altitude-based differences (Kanno et al. 2011).

Previous research based on household survey data from the same survey villages show that household consumption responds to agricultural income fluctuations that stem mainly from weather shocks (Sakurai et al. 2011). In addition, Miura, Kanno, and Sakurai (2012) report that farmers compensate for food shortages due to flooding by dissaving cattle as well as small livestock such as pigs and goats. This *ex post* coping strategy is very costly in terms of forgone future income, because livestock, especially cattle, are important productive assets in the study area. These findings suggest that local farmers do not have access to a complete risk-sharing mechanism. In addition, households in the study villages cannot overcome economic difficulties without missing opportunities to earn more income; moreover, the adoption in this area of inputs by which to achieve higher yields—such as chemical fertilizers and pesticides—is limited. Assessments from early field visits in May 2012 reveal that about one-half of the interviewed farmers had not applied any fertilizer to their plots during the 2011/12 agricultural season, irrespective of the government's policy of providing these at

[7] The choice of study sites and survey villages are based on a village census conducted in 2007. Refer to Sakurai (2008) for more information.

subsidized prices. Thus, these previous results provide a natural motivation to introduce weather index insurance to rural smallholders in the region. Especially, the provision of formal insurance could be a promising policy tool by which they can protect their productive assets, such as cattle, in the aftermath of weather shocks.

2.2. Village census: July 2012

This study utilizes three different datasets from the nine villages in the study area. We will provide the details of each survey, one by one. The first survey is a village census that was executed in July 2012. The census sought to survey all the households residing in the nine aforementioned villages; detailed information was collected from 440 households in total. The questionnaire used in the census asked about agricultural activities in the 2011/12 agricultural season, and also asked for demographic information. The information in this dataset is used for the orthogonality test of a randomized treatment in the following survey. In addition, variables from this census are used as baseline control variables in the regression analysis.[8]

2.3. Insurance product

We introduced a new insurance contract to the study villages, in collaboration with the Zambia Agriculture Research Institute (ZARI) and the Zambia Meteorological Department. The designed insurance contract is a type of index-based insurance, and it pays an insurance payout based on an objective indicator that highly correlates with income loss incurred by policyholders. This insurance type might not have problems associated with both moral hazard and adverse selection, both of which are often seen with indemnity-type insurance like crop insurance.

To work in line with local farmer perceptions, in May 2012 and prior to the introduction of the insurance contract, we informally asked about 50 farmers how frequently they experience drought. Their response was that over 10 years, they experienced about 3.23 years of drought, on average. In addition, according to information gathered through informal interviews with farmers, they perceive that their maize yield on average are approximately 1,400 kg/ha in a normal year and 400 kg/ha in a drought year, which means that their “average” drought reduces maize yield by about 1 tonne/ha. The same questions were posed to our sample farmers in October 2012, and qualitatively identical responses were confirmed (Table 1). In addition, from the informal interviews, we learned that the survey farmers consider heavy rainfall the main concern at the beginning of the rainy season, especially when they are sowing maize seeds. In fact, floods in December 2007 washed away land, forcing them to replant maize seeds (Miura, Kanno, and Sakurai 2012). The farmers were also anxious about there being too little rainfall in the flowering stage, in January and February.

Based on these field observations, we determined thresholds for the insurance contract, using rainfall data gathered at the Choma Meteorological Station of the Zambia Meteorological

[8] However, census data were not available prior to the randomization, and so we were not able to confirm *ex ante* the orthogonality between assignments to treatment and control households.

Department (Mochipapa) to generate the insurance index. The Choma Meteorological Station is 35–55 km from the study villages.[9] To design a suitable insurance contract, we needed to define “extreme weather” events for our study area. For this purpose, we undertook a descriptive analysis of the relationship between precipitation and maize yields. For precipitation, historical rainfall data at the Choma Meteorological Station were used. Following the basic division of seasons in Zambia, rainfall amounts between November and the following April were calculated for each agricultural year; for information on annual agricultural production, we exploited Crop Forecast Survey (CFS) data of the Southern Province, collected by the Central Statistical Office. It is important to note that the CFS data provided only predictions of agricultural production based on several factors, such as land. The study period was the 36 years from 1975/76 to 2010/11. Since the survey villages belong to either Choma or Sinazongwe District in the Southern Province, we pooled yield data from both districts. Unfortunately, CFS data from Sinazongwe District were available only since the 1993/94 agricultural year. In addition, in both districts, there were a few missing observations during the study period. Given these data limitations, the available number of observations for the analysis was reduced to 51 district-years.

Figure 1 illustrates maize yields and rainfall amounts in both districts since the 1975/76 agricultural year. Maize yield at the district level has been stagnant in magnitude and has widely fluctuated. As can be seen, these fluctuations could relate to rainfall amounts. The relationship between maize yield and rainfall seems to have an inverted-U shape, as agricultural production was found to generally decline in years in which there was either a relatively high or low rainfall amount. To see this point more quantitatively, maize yields in tonnes per hectare were regressed on the actual rainfall amounts and the other controls. As for the right-hand-side variable, we added a linear time trend, which is set to the first available year (=1975/76) as 0, into the regression model; we did this to control data quality in the maize yield data. The estimation results are shown in Table 2. As expected, total rainfall amounts during a rainy season have a statistically significant impact on maize production: in this case, its impact had an inverted-U shape with a peak at about 820 mm (column (1)).

However, in using the total rainfall amounts in an agricultural season as an index, we may fail to capture the distribution of rainfall in the season. As discussed, local farmers specifically care about rainfall amounts during the planting season (December) and in the flowering season (January and February). While taking into account rainfall distribution across months, maize yield is regressed separately, on rainfall amounts in December and on rainfall amounts in the flowering season. Column (2) of Table 2 reports the estimation results: consistent with farmers’ perceptions, these two rainfall amounts were found to have a statistically significant association with maize yield. Given

[9] Compared to relevant experiments in developing countries, the distances from the reference weather station might be relatively far. For example, Karlan et al. (2014; Appendix Table 2) uses five weather stations as a reference for a rainfall index insurance product, and their mean distances to farmer homesteads range from 6.7 to 32.8 km. Obviously, using an index at a remote weather station could in turn weaken the predictive power regarding the farmers’ loss. However, given the shortage of weather stations in the study area, we needed to rely on the Choma weather station, the nearest one to the survey villages. Although we show that the correlation between crop yield and rainfall at the station was sufficiently high to use the recorded amount as an index for the insurance contract, investigating the impacts of the distance on insurance demand would be a promising area of future research.

this result, the threshold of the insurance contract was based on rainfall amounts in different periods. Since farmers perceived the probability of drought as about 30–35%, we determined cut-off values so that the frequency of defined weather shocks was at the same level. As a result, we defined "drought" as a season whose total rainfall during the flowering season (January and February) is below 280 mm. To capture the hazardous effect of heavy rainfall in December, we also defined "flood" as a season whose total rainfall in December exceeds 300 mm. As Table 3 reports, the likelihood of "drought" and "flood" was found to be 36% and 11%, respectively, in the period between the 1975/76 and 2010/11 agricultural years. The frequency of "drought" had been fairly stable over the period, at above 30%. On the other hand, the frequency of "flood" had not been stable, since "floods" took place less frequently than "droughts." However, the lower bound of the frequency of "flood" seemed to be at around 3%. Using these definitions, the estimation result in column (3) of Table 2 confirms that these defined weather events reduce maize yield by 0.9 tonnes/ha in a "drought" year and by 1 tonne/ha in a "flood" year.[10] It is important to note that the reductions in maize yield due to these defined weather events at the district level almost coincide with the local farmers' expected crop loss due to what they perceived as drought.

These definitions of "drought" and "flood" were used in the insurance policy that we introduced to the farmers. Specifically, the defined condition under which a farmer would receive an insurance payout was if the total rainfall recorded at the Choma weather station of the Zambia Meteorological Department exceeded 300 mm in December 2012 or was less than 280 mm in the subsequent flowering season (January and February 2013). If this condition were to hold, the policyholder would receive insurance money in March 2013. In contrast, if the condition was not satisfied, the policyholder would receive nothing. The price of each insurance contract was set at 5 Zambian kwacha (ZMW) (approximately USD1) per contract.[11] The purchasing unit was not dependent on either the land holdings or the operation land size of the buyer. Since the average wage for agricultural casual labor was assessed as approximately ZMW10 per day, the premium was set to one that was affordable for local farmers. For the insurance contract to be actuarially fair, the premium rate was set at 33%, based on historical rainfall data over the latest 35 years (Table 3).[12] This means that if a farmer were to pay ZMW10 in October 2012, and if the rainfall in December were above 300 mm ("flood") or the total rainfall during the flowering season were less 280 mm ("drought"), he or she would receive ZMW30 in March 2013. Hence, we designed the trigger events and the premium rate so that they were reasonable for the local farmers, in terms not only of the magnitude of crop loss, but also the frequency of weather shocks.

As is the case in the rural areas of other developing countries, insurance was found to be new to the local people of the study villages. It was unclear, whether the farmers there would know how

[10] As shown in Appendix Table 1, the same exercise with the limited sample after the 1990/91 agricultural year reports that this trend has not changed in more recent years.

[11] Zambia implemented a new currency on January 1, 2013. The new Zambian kwacha (ZMW) was introduced at the rate of 1,000 old kwacha (ZMK) = ZMW1. Throughout this study, we use the current description of Zambian kwacha. In 2011 and 2012, USD1 was equal to approximately ZMW5.2.

[12] According to Table 3, the premium rate of 33% was actuarially fair—or at least actuarially *favorable*—for policyholders, because the lower bound of likelihood of "drought" and "flood" was around 33%.

this financial product works. To reduce their anxiety as much as possible, we tried to simplify the insurance contract so that they could understand it more easily. Thus, the insurance contract was based simply on a dichotomous condition, rather than on a more complex design involving, for example, a linear relationship between weather index and insurance payout. Please note that such simplification could induce an increase in the likelihood of the state where farmers experienced bad weather but there was no insurance payout. In the literature, this “worst state” is called basis risk. However, given their average level of financial literacy, we concluded that the advantage of such a simplification would outweigh its potential disadvantage. We wish also to emphasize that we set the premium that was affordable even for worse-off farmers. This price-setting was motivated by our speculation that one of the possible impediments to taking advantage of weather index insurance might stem from the indivisibility of the insurance contract and a high premium.

Compared to those in previous studies, another feature of the insurance contract in the current study was its small insurance payout with high probability. Although the insurance money to be received in the case of defined weather events was comparatively small due to the high probability of payout, the impacts of the insurance payout on the insured farmer’s livelihood were expected *not* to be small. The highly frequent occurrence of heavy rainfall or drought in a particular period forces local farmers to recultivate plots and replant maize seeds. The cost of new maize seed was found, at most, to be ZMW120; this could be covered by eight units of weather index insurance.[13] To source the money needed to fund the cost of this seed, uninsured farmers could sell one goat or six chickens, since the average unit values for goats and chickens are ZMW120 and ZMW20, respectively. In another scenario, uninsured farmers might choose to replant recycled seeds and generate lower harvest yields than if they had used new seed instead.[14] If a farmer were insured, an insurance payout could allow him or her to buy a fair amount of new maize seeds. Thus, such insurance seems to be in high demand in areas where agricultural production are completely rain-fed, like rural Zambia.

In summary, the weather index insurance studied here was not meant to compensate total income losses from rare and catastrophic weather shocks, but to provide sufficient compensation to allow insured farmers to replant maize seeds if there were rainfall failure at the early stage of the rainy season.

2.4. Insurance sales: October 2012

The second dataset used in this study was collected in October 2012, just before the start of the agricultural season. The research project’s interests are both actual demand for the aforementioned weather insurance and its impact on agricultural investment behavior. For this purpose, we randomly selected 160 households from the villager lists in the July 2012 village census. We then provided the heads of the selected households the opportunity to purchase the insurance product. We also

[13] The average cost of chemical fertilizer, such as D Compound and urea, per 50kg bag was found to be ZMW200.

[14] In our sample, recycled seeds were used in more than one-half of the plots. They were traditional seed varieties in most of the cases.

conducted randomization at this time, by supplying the sampled household heads free insurance, in addition to the amount of actual insurance demand. Hence, randomization occurred at the household level.[15]

Trained enumerators visited each household in October 2012. In our study area, the household head is considered the main decision-maker of the household, and so the participants of this survey were restricted only to the household heads; for this reason, most of the participants are male, save for widows who are household heads. First, the enumerators explained the insurance contract to the household head, left a copy of a leaflet visually explaining it, and informed him or her that insurance sales would take place at a designated place—usually the village head's place—approximately 10 days in the future. Note that the enumerator encouraged the household head to come, even if he or she was not interested in purchasing insurance. This instruction was meant to make it possible to analyze the behavioral changes of those who did not buy the insurance, by giving them free insurance payouts. Additionally, the enumerators told the survey participants that if they were interested in the insurance, they should bring enough money for the purchase. In addition to explaining the insurance contract, the enumerators conducted a household interview to collect demographic information and elicit a risk-preference parameter, in line with the methodology of Binswanger (1980). The game to elicit a risk preference was incentivized with actual winnings, the details of which will be provided later. The surveyed household heads were informed that they would get paid for the winnings at the time of the insurance sale.

After about 10 days of door-to-door visits, we held a "sales" day for each village. First of all, an enumerator asked each household head how many insurance units he or she wanted to purchase. Then, each participant paid money in accordance with his or her demand. At that time, he or she could use the winnings of the Binswanger game for the payment, if he or she had won. After receiving the money from the household head, the enumerator explained that additional free insurance payouts would be added, according to the sum of two dice that the surveyed farmer threw. The details of this treatment are summarized in Table 4. Based on the sum of the dice, we categorized the sample into four groups. Theoretically, the probability of receiving each treatment is the same, and equal to 25% among categories. As can be seen in Table 4, the households in treatment group 1 received an additional ZMW75, apart from their original insurance payout. For example, if a farmer purchased two units of the insurance contract and the sum of his or her thrown dice was 2, he or she would receive ZMW105 (=3*10+75) if either the predefined "drought" or "flood" were to happen. In the same fashion, the households in treatment groups 2 and 3 were given ZMW50 and ZMW25, respectively, as additional free insurance payouts. On the other hand, the households in control group 1 received no additional free insurance payout. Note that the final number of

[15] In our experimental design, control households might benefit from the free insurance provisions to treatment households through conventional risk-sharing networks within the village. Since we cannot fully exclude the possibility of such spillover effects, our reported treatment effects in the following sections might be weakly detected and underestimated in magnitude. An empirical test for the spillover effect is left for future work.

households was not identical across all treatment groups, on account of the randomization methodology used.

Unfortunately, at the time of writing, we have not conducted a household survey of those who were supposed to be in the other control group (control group 2) that were not offered the door-to-door insurance marketing, due to time constraints. Especially, we have not provided these control households small cash to control for the potential income effect of the free insurance provision on agricultural investments. Though this could be a limitation, we argue that the income effects would be negligible in magnitude. The monetary amounts received by treatment households were at most ZMW25, in the case of ZMW75 free insurance, equivalent to only about one fifth of the average cost of new maize seed, ZMW120. Given the tiny amounts of the free insurance provisions to treatment groups, our reported treatment effects in the latter sections would come mainly from insurance effects rather than income effects.

2.5. Reporting result: March 2013

In March 2013, one of the authors, along with ZARI personnel, visited the study villages to inform the survey participants of whether or not an insurance payout would happen. The rainfall index at the Choma Meteorological Station indicated that the 2012/13 agricultural year was a "normal" one, as the recorded total rainfall amount during December 2012 was 200 mm and that during the flowering season was 510.7 mm. Thus, no payouts were made.[16]

2.6. Follow-up survey: June 2013

The main purpose of this study was to measure the impact of the introduced insurance contract on the choice of agricultural technologies. To obtain information on agricultural activities during the 2012/13 rainy season, we successfully collected data in June 2013 from 154 of the 160 original households. In addition to the 154 households, we added 55 households in control group 2 to the survey sample as additional control households that were not offered the door-to-door insurance marketing in October 2012. They were also randomly selected from the villager lists in the July 2012 village census. Thus, the total sample size was 209 households. In the survey, trained enumerators collected information on agricultural production for the 2012/13 agricultural season, including field characteristics, seed characteristics, labor inputs, chemical use, and harvest amounts. One feature of this survey was that the field IDs were fixed to be the same as those used in the 2012 July Village Census Survey, in order to construct plot-level panel data and trace them easily during empirical analysis. Additionally, we collected detailed information about consumption, money transfers, livestock transactions, and household assets, as well as demographics.

2.7. Orthogonality test

[16] At the end of the multi-year research project (May 2014), we returned to the surveyed farmers their premiums, based on our past sales records. However, during the intervention, this was kept a secret from local farmers, to avoid having their behavioral changes be affected by expectations of having their premiums returned to them.

With respect to exogenous variation in insurance payout in the adverse states, we would not expect to observe statistically significant differences among any characteristics of households across the treatment categories, ranging from the group that received ZMW75 of free insurance money to another group that received nothing. To verify this systematically, standard orthogonality tests were conducted; their results are shown in Table 5. Table 5 reports descriptive statistics for selected household characteristics from the July 2012 village census, the results of an F-test from individual regressions of each household variable on a set of five treatment categorical dummies (column (6)), and those of an F-test from a regression of assignment to each treatment categorical dummy on the full set of covariates (bottom row). There are two caveats to bear in mind when interpreting empirical results in the following sections. First, we found a statistically significant difference in family size across treatment assignments; this stemmed from a significant difference in the number of male children (F-statistics = 2.98; *p*-value = 0.02). Thus, the number of children in a household, as well as the number of male and female adults therein, should be controlled for in the main regression. Second, the imbalance indicated a trend toward fewer family labor inputs in the two control groups; this would stem mainly from the unbalanced family size across the categories. Hence, this issue could be addressed to some extent by controlling for family size. To address the concern further, in Section 6, we also check the robustness of the main empirical results by controlling for these baseline values of outcome variables.

3. Descriptive analysis of demand for weather index insurance

3.1. Insurance demand

This section presents estimation results concerning the demand for insurance contracts. The analysis presented here is solely for descriptive purposes. Our goal in this section is to understand which observable variable was important to insurance uptake. The results obtained here gave us insights for building an empirical model, as detailed in the subsequent sections and which we used to measure the causal impacts of the insurance on agricultural activities. To achieve the current goal, we focused on the sample of households who had door-to-door insurance marketing in October 2012. The available number of observations in the sample was 160 agricultural households.

Figure 2 shows the result of insurance uptake in October 2012. For comparison purposes, Figure 2 also presents the results of insurance sales in November 2011.[17] The 2012 insurance sales resulted in 399 insurance policies sold, of which 377 were sold to individuals analyzed in this study.[18] The uptake rates exceeded 90% in both years—a finding different from that seen in the literature (Giné, Townsend, and Vickery 2008; Cole et al. 2013; McIntosh, Sarris, and Papadopoulos

[17] Although the unit price of the 2011 sales was the same as that of the 2012 sales (ZMW5), the contract design was different. The 2011 insurance contract used the total rainfall during the rainy season (November–April) as an index, and set 600 mm and 1,000 mm as the drought and flood thresholds, respectively. Referring to historical rainfall data, we defined 20% as the premium rate for the 2011 sales. In November 2011, we conducted both household interviews and insurance sales. Since it was the first year and we were not completely sure as to whether local farmers would voice any demand for the insurance product, the sample households were not randomly chosen. For this reason, this study used results from the 2011 insurance sales, but only for limited purposes.

[18] We did not limited purchasing opportunities to the sampled households: any villager from any of the three study villages could buy it, if he or she wanted.

2013).[19] The averages (standard deviations) of insurance uptake were 2.86 (3.09) units in the first year and 2.36 (1.90) units in the second year. One of the likely reasons for this reduction in demand might have been the lack of payout in the first year; another potential factor was that the sample in the first year was not randomly selected, and this may have biased the sales result. It is important to note that in both years, the proportion of farmers who purchased more than four units was not very high. As Hill, Hoddinott, and Kumar (2013) point out, such trial behavior can be observed in the decision to adopt an unfamiliar technology, as is theoretically predicted by a Bayesian model of learning about a new technology. The purchase of a small number of insurance units may reflect farmers' unclear perceptions of the benefits of the insurance contracts. In summary, although uptake rates were astonishingly high, the average insurance money that the farmer would receive in the case of a defined "drought" or "flood" was not enough to compensate for a total loss from weather shocks. However, the payouts would help insured farmers cover the cost of replanting maize crop whenever such frequent weather shocks did occur.

3.2. Explanatory variables

The question to be tackled here pertains to what obstacles rural farmers face in taking up insurance. By referencing the findings in the literature, we explain in this section the potential determinants of insurance demand. Obviously, previous experience can affect one's current decision-making with regards to the purchase of insurance (Cole, Stein, and Tobacman 2014; Karlan et al. 2014). To control for this, a dummy variable that took the value of 1 if the households were given the chance to buy the insurance contract in November 2011 was included in the regression equation.

In addition, the literature has shown that the demand for weather insurance correlates with risk preferences.[20] Specifically, a negative coefficient on risk aversion—which has the opposite sign of what we would expect for a risk-reducing financial product—has been frequently reported. This tendency is also akin to the decision to adopt a new technology, as empirical studies on technology adoption have long found that risk-averse households are less likely to be the first adopters of new technology. To test this in our setting, we elicited attitudes towards risk among the household heads, in line with the methodology of Binswanger (1980). The exact method of its elicitation is as follows. The enumerator showed a surveyed household head six alternatives; they explained that winnings were dependent on the result of a coin toss made by the enumerator, that the winnings differed among options, and that the winnings would be paid on the insurance sales day. The results are summarized in Table 6. The difference in expected returns divided by the difference in risks with a safer option ($\Delta E/\Delta risk$ in Table 6) was calculated for each alternative, and the values were used as a risk-preference variable in the regression equation.

Liquidity constraints constituted another possible impediment to insurance uptake. The main reason for not buying insurance in the similar pilot project was a lack of money to buy it (Cole et al.

[19] However, the premium differed among the projects. Most of the previous projects set the premium at around USD20, to create an insurance product that completely covered income loss. As will be seen, the demand for such coverage was also very low in our case.
[20] See Clarke (2011) for a theoretical example and Cole et al. (2013) as an empirical example, for instance.

2013). It is natural to think of household asset values as a good proxy for liquidity constraint. In addition, we exploited the amount of winnings—a byproduct of Binswanger's lottery—as an exogenous variation of income, because following the farmer's lottery selection based on his or her risk preferences, the winnings were randomly decided by the enumerator's coin toss. Thus, adding the amount of winnings along with the measure of risk preference to the vector of the right-hand-side variables provided us with another test of the importance of liquidity constraints in insurance demand.

Another potential constraint was the farmers' poor understanding of the general concept of insurance, the specific content of our insurance contract, or both. As was pointed out, insurance is a completely new concept to the most of the sample households. The literature also argues that it is very difficult for rural farmers, who are often less educated, to accurately grasp the concept of insurance, and this can lead to a low reported uptake rate. This possibility also seems to be the case in the current study area, where there are no local financial institutions (e.g., banks). To measure their understanding level, we asked farmers some simple questions about our insurance contract. Moreover, we asked them three arithmetic questions (addition and multiplication) to assess their general arithmetic calculation skills. Details of the questions, the proportions of farmers who provided correct answers, and the respective average levels of insurance demand are summarized in Table 7. As expected, a person who gave us the right answer was more likely to exhibit a higher demand for the insurance contract than a person who gave us the wrong answer; their differences in the average of demand were statistically significant, except with respect to the first question, which is about basis risk. In the regression, we separately added the number of correct answers to the questions regarding the insurance contract and the number of correct answers to the arithmetic questions to the vector of the explanatory variables.

In addition, the household heads' trust of the insurance providers mattered. More concretely, we needed to consider the heterogeneous magnitude of trust toward ZARI and our research project team among the sample households. To construct the trust index used in the regression analysis, we assumed that the farmers' trust was dependent on their frequency of interaction with ZARI and with us prior to the insurance sales. Since November 2007, some farmers in the sample had become very familiar with us, through our execution in the past of a four-year household weekly survey. To capture the magnitude of trust, the regression included group dummies with respect to sample stratification. Specifically, the sample was classified into the following three groups. The first group (Group 1) comprised households from whom the previous research project had collected weekly data since November 2007.[21] On account of the relatively long relationship its members had with ZARI and us, Group 1 was expected to have a certain level of trust with us. Households in the second group (Group 2) were randomly chosen from the same five villages as Group 1; however, they had not participated in our previous research project. Nonetheless, the households in Group 2 had also interacted with us since 2007 (e.g., village meetings), although their interactions were much less

[21] Miura, Kanno, and Sakurai (2012) describe the details of this survey.

frequent than those of Group 1. The third group (Group 3) comprised a group of households from four different villages within the same study area; thus, we speculated that the trust level towards ZARI and us was highest among those in Group 1, followed by those in Group 2 and those in Group 3.

Perceived probability of whether or not an insurance payout would occur could have differed amongst the respondents. Such perceptions would naturally depend on how well they knew the probability distribution of rainfall at the Choma weather station—in other words, the difference in rainfall between the weather station and their plots—and how strong their expectations were vis-à-vis each weather event (i.e., “drought”, “flood”, and “normal” seasons). As a proxy for the first factor, we used a dummy variable indicating whether they had a relative in Choma. As for the second factor, the household survey elicited subjective probabilities for the three weather events. To do so, we applied the methodology of Hill et al. (2013), wherein the enumerator used pictures indicating each weather event and asked the respondents to allocate 10 bottle caps among the pictures in accordance with how likely, in their estimation, each weather type was to occur in the incoming rainy season. Table 8 presents the summary statistics of farmers’ perceptions for each study site. As seen in that table, the farmers thought that rainfall would not be normal with a probability exceeding 50%, regardless of the study site. In the regression, we used the number of bottle caps on the “normal” year picture as a measure of the prediction of the trigger events in the insurance contract. In addition, we tried to capture heterogeneity in the information useful for their predictions by including a dummy that took the value of 1 if farmers had heard a formal weather forecast about the incoming rainy season, mainly through radio broadcasts. In the same spirit, a dummy variable pertaining to whether farmers observed something useful for forecasting weather—such as the maturation level of certain fruits, or stars in the sky—was also included in the vector of explanatory variables, as these traditional ways of forecasting weather were very commonly used in the study villages (Kanno 2008; Lybbert et al. 2007).

Precautionary saving may have had a relationship with the demand for weather index insurance. Like the case of households in another rural African area, local people in the research site considered keeping livestock—especially small livestock such as pigs and goats—as a main way of precautionary saving (Miura, Kanno and Sakurai 2012). It is not difficult to sell small livestock to villagers or livestock traders, and so in our study area, the liquidity of these assets was fairly high. Risk-sharing networks consisting of relatives and friends who helped them cope with difficulties in times of need would constitute another important risk-coping tool. Generally speaking, it was not possible to control for the number of people who can be helpful, and it was not appropriate to think that having access to such a risk-sharing network would be exogenously given. If a household maintained an optimal amount of small livestock for precautionary purposes or was already a member of an effective risk-sharing network, and these ways were cost-effective relative to the weather index insurance, then demand for the insurance contract would be weak. If this were the case, the coefficients on proxies for existing risk-coping mechanisms would take negative values.

Conversely, if the weather index insurance were more cost-effective than keeping small livestock or engaging in risk-sharing networks, then the survey participants would want to replace those mechanisms with formal insurance. In this case, weather index insurance could be considered a substitute for existing risk-management mechanisms, and so the coefficients on these variables were expected to have positive signs.[22] However, we also saw a positive sign when a household had a desire to increase the number of types of risk management tools, and thereby enhance the effectiveness of its portfolio by diversifying the risk inherent in each risk-coping mechanism. In other words, households may consider weather index insurance an effective complement of existing risk-management mechanisms, as discussed in Mobarak and Rosenzweig (2012). In this case, the demand for insurance would increase with prior access to these mechanisms, and the coefficients on these variables were also expected to bear positive signs. Thus, the relationship between such kinds of risk-management activities and the demand for the insurance was ambiguous *ex ante*, and thus posed an important empirical question. To test for this, for each household, we calculated the value of its small livestock and the number of people, such as relatives and friends, whom the household could call upon in times of need; these were added to the regression equation.

Finally, it is worth noting that the theoretically recognized disadvantage of index insurance is the presence of basis risk (Clarke 2011; Carter 2012; Miranda and Farrin 2012). In the literature, basis risk refers to the probability of there being no insurance payment when farmers experience crop failure because of an imperfect correlation between the reference index and crop loss. However, in an empirical setting, it is difficult to index the magnitude of basis risk. Our strategy with regard to this was to add site dummies to capture a portion of the basis risk through the geographical distance between the weather station and each farmer’s plots, as there was only one reference weather station. Of course, this strategy could not identify the causal effect of basis risk on insurance demand, but for our preliminary purposes, it sufficed to accurately control for this factor.[23]

In summary, in analysis undertaken to explore the determinants of insurance demand, the number of insurance units that a household head purchased was used as the dependent variable in the regression equations. To explain this, we added the elicited risk preference, the winnings from the Binswanger-style lottery game, the number of correct answers to the insurance questions, the number of correct answers to the arithmetic questions, the value of physical assets and large livestock, the value of small-livestock holdings, the number of people who could be called upon in times of need, a dummy variable about whether the household has relatives in Choma, the perceived probability of a normal year (i.e., the number of bottle caps on the “normal year” picture), a dummy about whether a household gathered information from formal weather forecasts, a dummy about whether household

[22] With respect to this, demand analysis does not suffice. For a complete test, we also need to look at household adjustment behavior following the adoption of insurance. To do so, we verify in Section 5 whether households started to sell small livestock.

[23] We installed automatic rainfall data loggers at representative plots of some of the respondents, and collected field-level rainfall data for five agricultural seasons (2007/08–2012/13). By using rainfall data from the plots as well as from the weather station, and calculating direct measurements of basis risk for each farmer, future research will empirically show the impact of basis risk on demand for our weather index insurance.

observed anything useful for weather forecasts, group dummies, information on household head (e.g., age and gender), and site dummies.

3.3. Estimation results

Table 9 presents regression results with regard to the determinants of insurance uptake in October 2012. The dependent variables in columns (1)–(3) pertain to the number of insurance contracts that a farmer purchased. The dependent variables in the second set of three columns pertain to a dummy variable indicating the purchase of four or more insurance units. The reasoning for using four units as a threshold is that four units of insurance would provide insured farmers with a payout of ZMW60—an amount sufficiently large to cover the cost of a 15-kg bag of maize seeds for a 1-ha plot.

First of all, having had past experience with insurance increases the probability of purchasing more than four units of insurance (shown in columns (4)–(6)), although the effects are not statistically significant throughout the full range (columns (1)–(3)). The favorable effect of past experience might be explained by an increase in understanding of the insurance contract among second-time buyers. On the other hand, the coefficients on group dummies are not statistically significant at all, suggesting that trust towards the insurance provider does not matter during the first purchase of insurance, although trust generation is generally a dynamic process.

In column (1), the coefficient on risk preference measure is statistically significant and negative; this is consistent with the findings in the literature (e.g., Cole et al. 2013). However, a one-standard-deviation increase in risk-preference measures reduces insurance demand by only 0.34 units, thus indicating that the effect is not economically significant. In addition, this result might be reflected in the lottery game winnings. To examine this point, while column (2) reports the estimation results while replacing the measure of risk aversion with the amount of winnings, column (3) reports the estimation results of a regression that includes both variables. As can be seen in columns (2) and (3), the effect of winnings is statistically significant by itself, and once the amount of winnings is included, the statistically significant effect of risk preferences vanishes.[24] These results suggest that a small amount of disposable cash might be more important to insurance uptake than risk-related motives. However, the sum of the values of asset holdings and large livestock had no impact on insurance uptake, and this indicates that the statistically significant effect of the winnings might capture a different channel rather than a typical liquidity constraint channel.

In addition, Table 9 shows that subjective probabilities vis-à-vis upcoming weather and access to either formal or traditional weather forecasts had no significant relationship with insurance demand. On the other hand, the robust and statistically significant positive coefficient on having relatives in Choma provides suggestive evidence that people with more information on the

[24] Even when the choices, instead of the estimated value of risk aversion, were directly added to the right-hand-side variables without assuming any functional form of utility function, no significant result was deduced.

distribution of rainfall at the reference weather station (i.e., the Choma weather station) were more likely to purchase weather index insurance.

As can be seen in columns (1)–(3) of Table 9, we found a positive relationship between the understanding level of insurance contract and general calculation skills, and insurance demand. Thus, broadly speaking, educated farmers were more likely to purchase the insurance product. A similar finding is reported by Hill et al. (2013) from Ethiopia, and Cole et al. (2013) from India. However, as shown in columns (4)–(6), these variables do not explain well whether a meaningful number of insurance units were purchased. This observed pattern implies that although having a good understanding of insurance and arithmetic skills helped farmers take up insurance contracts, these were not in themselves sufficient conditions for purchasing valuable amounts of insurance.

With respect to precautionary saving, we include the quadratic terms for the value of small-livestock assets and the number of people who could be called upon in times of need, in order to allow their nonlinear relationship with the demand for insurance. Table 9 shows that the effect of small-livestock holdings on insurance demand is concave, with its peak at around ZMW3,200 based on the first three ordinary least squares (OLS) specifications and at ZMW2,000 based on the three Probit model specifications. These can be explained by two different hypotheses, as follows.[25] First, this could happen because the farmers had a desire to change the portfolio by replacing small-livestock savings with weather index insurance, since the weather index insurance was recognized as the more cost-effective risk-coping mechanism. Second, local farmers might simply have had a desire to diversify their risk-coping strategy, because they considered weather index insurance complementary to small-livestock holdings. To completely confirm which hypothesis dominates, it is important to determine whether the households with a greater number of small livestock started to dissave them after adopting the insurance. If this were observed, we could conclude that weather index insurance was considered a substitute for small-livestock holdings, and that weather index insurance was more cost-effective than self-insurance through small-livestock savings. Conversely, if they did not substantially reduce small-livestock holdings, this would serve as suggestive evidence that the weather index insurance might have been considered a complement in existing risk-coping strategies. Our test of whether small-livestock savings were crowded out or crowded in by the introduction of weather index insurance will be discussed in Subsection 5.2.

On the other hand, the coefficient on the number of people who can be called upon in times of need in columns (2) and (3) is negative and statistically significant. Since this variable was used as a proxy for access to a risk-sharing network, our interpretation is that those without access to a good risk-sharing network were more likely to take up the insurance contract. Thus, there is the strong possibility that weather index insurance might have been accepted as an alternative risk-coping tool by those without access to a risk-sharing network. However, the impact of a risk-sharing network on

[25] One might guess that the value of small livestock merely captures wealth effects on insurance demand. However, the estimation results of the regression excluding the value of small livestock holding still reveal an insignificant coefficient on the value of assets and cattle (not reported), suggesting that statistically significant coefficients on the value of small livestock capture the self-insurance channel.

insurance demand reverses in columns (4)–(6). Thus, the number of insurance contracts purchased by households with less social capital cannot sufficiently compensate for losses due to rainfall failure. Investigating impediments to the adoption of formal insurance among those currently excluded from previous social networks is left for future research.

Surprisingly, household wealth, indexed by the value of physical assets and large livestock, had no impact on the demand for insurance. The specification lacking the small-livestock value gave us quantitatively similar results (not reported). This insignificant effect might have resulted from the mixed potential impacts of wealth: on one hand, more affluent households can gain access to some consumption insurance against negative shocks, but on the other hand, they can easily buy weather index insurance if they want to adjust their current portfolio of risk-management tools. Thus, given our data, we can make no conclusion with respect to whether the insurance contract is a normal good.

In summary, the estimation results presented in this section show that having a weak understanding of insurance, poor arithmetic skills, and poor knowledge of rainfall distribution at the reference weather station prevented farmers from adopting insurance contracts. On the other hand, having small amounts of disposable cash might have encouraged farmers to take up weather index insurance. Moreover, existing risk-coping mechanisms—especially small-livestock savings—were found to have a close relationship with demand for weather index insurance.

Keeping these findings in mind, we move on to analysis of the effects of insurance provision on investment in higher-return, higher-risk technology.

4. Empirical strategy

4.1. Endogeneity problem

Given the randomly provided additional free insurance, the empirical strategy is relatively straightforward. However, we need to carefully treat an endogenous part of the insurance demand. To further clarify this issue, this section discusses an empirical strategy for regression analysis. The total insurance payout in the case of either "flood" or "drought" can be summarized as:

$$Total_{iv} = Free_{iv} + Purchase_{iv}, \tag{1}$$

where the subscript i represents the household, $Total_{iv}$ denotes total insurance payout that household i in village v receives in one of the adverse states (i.e., if either a "drought" or "flood" were to happen), $Free_{iv}$ is the insurance payout from the free insurance contracts received by household i in village v, and $Purchase_{iv}$ is the insurance payout from insurance contracts purchased by household i in village v.

The main regression analysis was done both at the maize-plot level and the aggregate household level.[26] We used as outcome variables the farmers' choices of agricultural technologies during the 2012/13 rainy season. The outcome variables in the analysis at the plot level included the

[26] The analysis here focuses on agricultural inputs at the maize-plot level, because almost all the sampled farmers cultivated maize, a staple food in the study area.

use of new maize seeds, the timing of planting maize seeds, the amount of fertilizer applications, and the amount of labor inputs by both family members and hired workers. On the other hand, the outcome variables in the analysis at the household level included the total size of cultivated land, the aggregate amount of fertilizer applications, and the aggregate amount of labor inputs by both family members and hired workers.

The structural equation of these outcome variables at the plot level can be formalized as:

$$y_{piv} = \beta_0 + \beta_T Total_{iv} + X_{piv}\beta_p + X_{iv}\beta_h + \sum I_v\beta_v + \mu_{piv}$$

$$y_{piv} = \beta_0 + \beta_T(Free_{iv} + Purchase_{iv}) + X_{piv}\beta_p + X_{iv}\beta_h + \sum I_v\beta_v + \mu_{piv}, \qquad (2)$$

where y_{piv} represents the outcome variable at plot *p* of household *i* in village *v*, X_{piv} is a vector of the land characteristics of plot *p*, X_{iv} is a vector of the household characteristics of household *i*, I_v is a village dummy for village *v*, and μ_{piv} is the unobservable random disturbance. For simplicity, assume the population orthogonality conditions $E(X_{piv}\mu_{piv}) = E(X_{iv}\mu_{piv}) = 0$ (i.e., both X_{piv} and X_{iv} are exogenous). The vector X_{piv} contains the topographical position of the land, the total land size, the distance to plot from home in minutes, and the self-reported soil quality. Information on X_{piv} as well as y_{piv} came from the 2013 follow-up survey. The factors in the vector X_{iv} will be discussed later, as the selection of controls depends on the determinants of endogenous insurance demand. The coefficient of interest is β_T, and it measures the causal impact of the weather index insurance contract on farmer's agricultural production behavior. If $E(Purchase_{iv}\mu_{piv}) = 0$ holds, the set of parameters of interest, including β_T, would be identified, and the OLS estimates would provide us with a consistent estimator of the parameters. However, $E(Purchase_{iv}\mu_{piv}) = 0$ is unlikely to be true in our setting, given the possible presence of unobservable household heterogeneity in μ_{piv}, which correlates with both $Purchase_{iv}$ and y_{piv}.[27] This is due to classical self-selection: if local farmers chose the value of $Purchase_{iv}$, their decision might have been related to factors unobservable to us. For example, if farmers with high-level agricultural operation skills or highly motivated farmers tended to purchase the insurance contracts more frequently than the average farmer, the asymptotic bias of the OLS estimate $\widehat{\beta_T}$ would be positive, and thus the impact of insurance provision on the choice of agricultural technologies would likely be overestimated.[28]

[27] Assume here that unobservable factors that correlate with $Purchase_{iv}$ are at the household level rather than at the plot level. In other words, once household-level unobservables have been controlled for, plot-level unobservable characteristics are found not to correlate with $Purchase_{iv}$. This assumption does not seem to be controversial, given that the endogenous variable $Purchase_{iv}$ is a household-level variable. In addition, even if there is serious bias due to unobservable plot characteristics, both the topographical position and self-reported soil quality work well as proxies for them, so that the asymptotic biases are smaller in magnitude than if these plot-level observables were omitted from the regression. However, since a direct test of the validity of this assumption is not available, this will be relaxed as a robustness check, utilizing plot-level panel data (not presented in this version).

[28] By the orthogonality conditions for all the observable explanatory variables except $Purchase_{iv}$, the unobservable factor does not correlate with them once the partial correlation of $Purchase_{iv}$ with the unobservable has been partialed out. Under this common assumption for simplification, plim $\widehat{\beta_T} = \beta_T + \gamma\frac{cov\,(q_{iv},\ Purchase_{iv})}{var\,(Purchase_{iv})}$, where q_{iv} represents the unobservable factors and γ is the coefficient on $Purchase_{iv}$ in the linear projection of q_{iv} onto the constant and $Purchase_{iv}$.

4.2. First-stage regression: determinants of insurance demand

To handle this typical endogenous problem, we relied on the IV approach and exploited exogenous variations in $Purchase_{iv}$. To proceed further, the reduced-form equation for the endogenous variable $Purchase_{iv}$ can be modeled as:

$$Purchase_{iv} = \alpha_0 + X_{piv}\alpha_p + X_{iv}\alpha_h + \sum I_v\alpha_v + Z_{iv}\theta + \nu_{iv}, \qquad (3)$$

where Z_{iv} is a vector of instruments and ν_{iv} is a linear projection error uncorrelated with each regressor in the reduced form (3). From equations (2) and (3), the endogeneity of $Purchase_{iv}$ arises if μ_{piv} correlates with ν_{iv}. The requirements for the IVs can be summarized as [1] $Cov(Z_{iv}, \mu_{piv})$ = 0 and [2] $\theta \neq 0$.

We selected the factors of X_{iv} from the village census data, and referred to the previous results regarding the determinants of insurance demand. The empirical challenge here was that the exact same variables as those in the previous regression equation were not available for households within the control group that were added in June 2013. Based on the previous empirical results, we needed to control for understating the level of insurance, general arithmetic skills, knowledge background about the rainfall distribution at the reference weather station, and value of small-livestock holdings as an existing risk-coping strategy. Since neither of the first two variables was available in the village census, the years of education of the household head was used as a proxy for them. As expected, we confirmed that the educational attainment of the household head positively and highly correlated with the number of correct answers to both types of questions in the limited sample of the October 2012 survey. In addition, fortunately, the village census had asked the surveyed farmers whether they had relatives in Choma, and the value of their small livestock. As before, we also added the square term of small-livestock value. As for the other controls, we tried to use the same variables as much as possible. In the end, the vector of the explanatory variables (X_{iv}) included, in addition to the four aforementioned variables, the gender of the household head, the age of the household head, the number of male adults, the number of female adults, the number of family children, the value of large livestock, the value of physical assets holdings, the number of people who could be called upon in times of need, and its squared term.

The natural instruments for $Purchase_{iv}$ (Z_{iv} in equation (3)) were D^t_{iv} and a dummy variable equal to unity for treatment households (i.e., surveyed households who had door-to-door marketing in October 2012), and 0 otherwise. Since the eligible households in the nine villages were randomly selected, D^t_{iv} should maintain the exclusion restriction condition. The other candidate was the amount of winnings of the Binswanger-style lottery, denoted by $Winning_{iv}$. As discussed before, the amount was based on each farmer's lottery choice, but the final amount was randomly determined by the enumerator's coin toss. In addition, we confirmed that risk preferences had only a negligible effect on insurance demand. Another justification could be that the study villagers were paid for their winnings at the time of village insurance sales, and they were allowed to directly use the winnings to pay for premiums. Moreover, the amounts were too small for winners to use them to purchase any agricultural inputs, but the winnings had a statistically significant positive association with insurance demand (Table 9). Given all these facts, $Winning_{iv}$ was plausibly excludable from the second-stage regression equation (2) and also satisfied the relevance condition for an IV, thus allowing us to use $Winning_{iv}$ as another instrument for $Purchase_{iv}$. In summary, $Purchase_{iv}$ is instrumented out by the two IVs: the October 2012 insurance sales survey dummy D_{iv}^{t} and the winnings of the Binswanger-style lottery $Winning_{iv}$.

Table 10 reports the first-stage regression results separately for plot-level analysis and household-level analysis. The F-statistics for the two IVs are sufficiently high to satisfy the relevance condition for a convincing IV.

4.3. Second-stage regression: effects of insurance on farmer behavior

Using the first-stage regression results, the second-stage regression estimates the impact of weather insurance on farmers' agricultural activities. To do so, we first derived control function (CF) estimators. We formulized the linear projection of μ_{piv} on ν_{iv} as

$$\mu_{piv} = \rho\nu_{iv} + \varepsilon_{piv}, \tag{4}$$

where ε_{piv} is a linear projection error that does not correlate with ν_{iv}. Note that ε_{piv} is also uncorrelated with the instruments Z_{iv}, as μ_{piv} and ν_{iv} both correlate with Z_{iv}. Denote the OLS residuals from the first-stage regression (3) by $\widehat{\nu_{iv}}$. Then, substituting (4) into (2) and replacing unobservable ν_{iv} with $\widehat{\nu_{iv}}$, we derived

$$y_{piv} = \beta_0 + \beta_T Total_{iv} + X_{piv}\beta_p + X_{iv}\beta_h + \sum I_v\beta_v + \rho\widehat{\nu_{iv}} + \varepsilon_{piv} \tag{5}$$

By regressing (5) by OLS, we consistently estimated all the parameters that include β_T, the causal impact of insurance provision on farmer's agricultural investments. The basic idea of the CF approach is that the inclusion of $\widehat{\nu_{iv}}$ controls for the endogeneity of $Total_{iv}$ in the original equation (2). Note that these CF estimators were identical to the 2SLS estimators. However, we adopted the CF approach, instead of the IV approach, because the magnitude of bias from the endogenous part of $Total_{iv}$ could be obtained. In addition, more importantly, the CF approach can be adapted to certain nonlinear models where the typical IV approach is not suitable for analysis. Since in the next section we use a dummy variable as an outcome variable (e.g., dummy equal to 1 if new maize seed is used, and 0 otherwise) and run the regression by Probit and Tobit, the CF approach is preferable. Because $\widehat{\nu_{iv}}$ is a generated regressor from the first-stage regression, we need to account for the sampling variation in $\widehat{\nu_{iv}}$ and correct the standard errors of each coefficient by the bootstrap sampling method.

5. Estimation results

5.1. Impacts of weather insurance on agricultural activities

Table 11 presents the estimation results for the impact of insurance provision on farmers' agricultural investments in risky inputs at plot level. Panel A shows results from the endogenous regression equation (2) without correcting biases that arise from the endogenous part of the insurance demand. All regressions included the household-level controls, the plot-level controls, and the village dummies. The dependent variables for each regression are specified at the head of the column. The dependent variables are chronologically ordered, based on the usual agricultural practice in the research area.

The estimation results in Panel A of Table 11 report the favorable impacts of the insurance contracts on the farmers' selection of agricultural technologies. First, compared to households without insurance, households with insurance were found to cultivate larger sizes of maize plots. The quantitative impact of insurance is not negligible: the increase in total insurance payout by ZMW80 would prompt farmers to cultivate a 0.18-ha larger maize plot than before; this amount was equal to 23% of the average maize plot size.[29] The same quantitative experiment revealed that a ZMW80 increase in total insurance payout would allow farmers to use new seeds at a 12% greater probability, plant maize seeds four days earlier, apply an additional 14 kg of urea, and allocate an additional 26 person-days of family labor. However, these results do not at all take into account the endogenous part of insurance demand.

Endogeneity issues are addressed by the CF approach, the results of which are shown in Panel B of Table 11. Column (1) of Panel B shows the same direction of insurance effects on the size of land operation. However, the coefficient was comparatively smaller in magnitude. This observation implies that the coefficient obtained from the endogenous regression could give us an overestimated estimator, on account of unobservable omitted variables. In fact, the coefficient on the residual from the first-stage regression was statistically significant and positive, suggesting that there might be omitted-variable bias in the naïve regression shown in Panel A. As a result, the estimation results show that a ZMW80 increase in total insurance payout would induce farmers to increase the operation size of their maize fields by 0.10 ha per plot, or approximately 13% of the average maize plot size. Decision-making with respect to the size of land operation is a pure example of *ex ante* investment decisions, and so the results show the clear causal impact of weather insurance provision on a household's agricultural activities.

Upon finishing land preparation, farmers engage in seed-planting. The first criterion was whether farmers used new maize seed rather than ones harvested in the previous season ("recycled seed"). Informal interviews in the field determined that farmers recognized that the expected harvest amount when using recycled seed would be generally one-third that when using new maize seed.[30] Given this, the purchase and planting of new maize seed is a risky input in agricultural production, as farmers need to replant maize seeds if rainfall fails at the beginning of the rainy season. As can be seen in column (2) of Panel B, the statistical significance level of the coefficient on total insurance payout vanished after taking into account the endogeneity of insurance demand. The second criterion

[29] A ZMW80 increase in total insurance payout is used in the quantitative experiments, because in our sample the most frequent total insurance payouts is ZMW0, at its 25th percentile, while the second most frequent one is 80ZMW, close to its 75th percentile value.

[30] However, great care should be taken in interpreting this observation from the informal interview, as all recycled seeds could be traditional varieties, and their low yields might simply be a reflection of differences in varieties. The point being made here is that the mere sowing of new seeds is comparatively risky.

was whether farmers used early-maturity maize seeds. In a drought-prone area like our study site, the seed's maturity level is important for reducing the risk of large losses on account of drought. There are roughly three levels of maturity. An early/medium-maturity variety was recommended to farmers for planting by agricultural extension officers, given the frequent occurrence of drought in the study region. For the early-maturity variety, 100–120 days pass between seeding and harvest. The estimated coefficient on the dummy equal to 1 if an early-maturity variety was used was also statistically insignificant. Taken together with the previous results regarding investments in new seed, it seems that weather index insurance did not induce agricultural households to invest in maize seeds. Ideally, decision-making with respect to maize seeds should be treated jointly, and this might give rise to these insignificant effects. The sign conditions were satisfied in these two cases, and these two effects were marginally significant, thus providing suggestive evidence of the impact of insurance on investments in maize seeds.

The timing of maize seed-planting is another important aspect of agricultural technologies at the planting stage. Local farmers generally plant maize as early as possible after the rainy season begins, and this recognition on the part of farmers aligned with evidence from farm trials in the same study villages. Shimono et al. (2012) show that delaying sowing by 10–20 days can reduce maize yields by 19%—equivalently, 125 kg/ha, on average—compared to the control plot sowed on a "normal" date based on the decisions of local farmers, in a two-year controlled experiment under local environmental and cultivation conditions. To measure the effect of insurance on the timing of planting, we constructed differences in the days between November 1 and the date when households planted maize seeds, and used this variable as an outcome variable. The estimation results with respect to this variable were found to be consistent with the theoretical prediction: once farmers were insured, they tended to plant seed earlier than before (column (4)). These results indicate that a ZMW80 increase in insurance payout would induce farmers to plant about five days earlier. Taken with the evidence regarding the positive impact of early planting on maize productivity from Shimono et al. (2012), there is the strong possibility that due to weather risk, farmers hesitate to plant early under incomplete insurance markets. Investment in seeding activities is another pure example of an *ex ante* investment decision before the realization of rainfall in the relevant agricultural season; thus, this serves as further evidence of the causal impact of weather insurance provision on investments in risky agricultural input.

Another important risky agricultural input is fertilizer. Despite its potentially high expected profitability, 40% of farmers in the sample did not apply any fertilizer during the 2011/12 agricultural season, before the insurance provision.[31,32] In the study area, there are two types of

[31] This number is from the 2011 village census. The adoption rates of fertilizer vary among villagers, partly because of the availability of co-operatives. If a farmer is a member of a co-operative, he or she can purchase fertilizer at a subsidized price that is much lower than the market price.

[32] However, the profitability of fertilizer in rural Africa is not clear in the literature. For example, Beaman et al. (2013) find no evidence that profits increased after providing free fertilizer to female rice farmers in Mali. Another piece of important evidence is in Suri (2011), who determined an underlying heterogeneity of profitability of fertilizer usage among farmers in Kenya. As positive evidence from a series of field trials, Duflo, Kremer, and Robinson (2008) report that rates of return on fertilizer use were about 70% in rural Kenya. At this time, we have no quantitative evidence regarding the profitability of fertilizer application at our study site.

common fertilizer: D Compound, which is used for basal dressing, and urea, which is used for top dressing. Hence, urea is generally applied one month after the application of D Compound, although farmers often do use them simultaneously. The amounts recommended by agricultural extension officers were the same, approximately one bottle cap per planting hole. Columns (5) and (6) of Table 11 list the amounts of D Compound and urea (each in kilograms), respectively, as a dependent variable. Since a large proportion of farmers did not use any fertilizer on their maize plots, Tobit estimation models are employed for the regression. As shown in column (5), the effects on the application of D Compound are not significant, but the sign of the coefficient is as expected. On the other hand, the Tobit estimation results regarding urea application amounts show that insured farmers tend to apply more urea, even after controlling for endogeneity in insurance demand; moreover, its quantitative impact is large. Based on the estimated result, a ZMW80 increase in insurance payout would induce farmers to apply approximately 9.7 kg more urea, which is equivalent to 35% of the average amount applied. A possible reason for the favorable evidence of investments in urea is that since the application of urea generally occurs after the application of D Compound, farmers could have more time to source the money to pay for urea. Please note that the magnitude of the coefficient became smaller in Panel B than that in Panel A in the case of urea, which implies the omitted-variable biases to be controlled for.

The final agricultural inputs analyzed here are labor inputs. Family labor inputs were measured as the product of the number of workers and working hours, and included all kinds of activities, such as cultivation, planting, weeding, and harvesting. Hired labor inputs were measured in terms of payments to hired labor, in ZMW; they included the booking cost of oxen for ploughing. As can be seen in columns (7) and (8), households with better insurance increased their family labor inputs in the fields, but did not change the amount of hired labor inputs. Regarding the magnitude of the impact on family labor inputs, a ZMW80 increase in insurance money in one of the adverse states was found to prompt an additional 25 person-days of family labor. In agricultural practices in the study area, labor inputs are in greatest demand at the seeding stage (i.e., land preparation and seeding). This important finding will be discussed soon, along with results regarding the impact on farmers' land operation.

In addition to these changes in agricultural inputs at the extensive margin, we were also interested in their changes at the intensive margin. To see this, the amounts of fertilizer and labor inputs per hectare were regressed on the same explanatory variables as in Table 11; Table 12 shows the estimation results. We found weather index insurance contracts to have no significant effect on their changes at the intensive margin; this suggested that farmers might increase fertilizer in association with an increase in the size of land operation, and that they did not intensify the application of fertilizer. Regarding labor inputs, the estimation result in column (3) shows that insured farmers increase the intensity of family labor inputs per plot, in addition to an increase in family labor inputs along with an increase in the size of land operation. These findings are especially unique, as these effects would be neglected in empirical analysis at the aggregate household level.

Now, we turn to analysis at household level. Table 13 shows regression results with various aggregate household-level outcome variables. Columns (1) and (2) of Table 13 report the estimation results with respect to the size of operated land and of operated maize land. The results therein suggest that insured households increased their total land operation size, mainly for maize fields, at a statistically significant level; this finding aligns with the previous estimation results at the plot level. Using the estimated coefficients in Panel B, a ZMW80 increase in insurance payout induced farmers to cultivate 0.33 ha more agricultural land and 0.28 ha more maize plots. Enlarging the operated field size can be considered a risky strategy in agriculture. Since land transactions are free among relatives or at a low cost on the site, such an increase in the size of operated land can be accompanied by an intensification of labor inputs, as seen in column (6) of Table 13. On the other hand, no statistically significant effects were detected with respect to fertilizer applications, although the sign conditions were consistent with expectations. These insignificant results regarding chemical fertilizer use might have stemmed from not making simultaneous decisions vis-à-vis the choice of plots for fertilizer applications.

The "flip side" of the expected weather insurance effects is that the farmers were discouraged from overinvesting in hedging inputs. Given the reported evidence that insured agricultural households cultivated larger maize plots, we could expect the magnitude of crop diversification to decline in response to an increase in maize production. The results of a direct test regarding this (not reported), however, indicated that the proportion of maize field did not statistically change. If another crop, such as cotton, was recognized as being more profitable, farmers could increase the operation size of such a crop more than that of maize and, as a result, could lower the proportion of operated maize land. Unfortunately, we did not have rigorous data that would allow us to calculate each crop's profitability—although cotton in general seems to be recognized by local farmers as a riskier crop than maize. However, this result still appeared to be natural, given the fact that almost all the surveyed households engage in maize production and there is a traditionally mono-cropping practice in some villages. In other words, the geographical constraint was too tight within the study area for farmers to shift in the short term from a safe crop (e.g., maize) production mode to a risky one (e.g., cotton).

5.2. Impacts of weather insurance on self-insurance

As argued previously, households in the rural areas of developing countries tend to keep livestock—especially small livestock, such as goats and pigs—for precautionary purposes. This form of saving cannot be efficient, as it precludes other opportunities to invest in more profitable assets or activities. Once climatic risk is mitigated by taking weather index insurance, households can start to reoptimize their amount of precautionary saving. Our empirical results on insurance demand show that households with more small livestock tend to purchase weather index insurance. This finding can be explained by two competing hypotheses. The first explanation is that households like to adjust their self-insurance portfolio, as weather index insurance is more cost-effective than keeping small livestock. If this hypothesis were true, we would see farmers' increased sales of small livestock following the introduction of insurance. A second possible explanation is that households like to increase the types of self-insurance that they leverage, in order to further diversify risk; as such, they consider weather index insurance a complement of small-livestock holdings. If this were the case, we would see an insignificant effect on small-livestock net sales following the introduction of insurance.

To empirically test these two competing explanations, we observed livestock transactions made by the survey participants just after the insurance was introduced. Doing so was required, if we were to disentangle what we wanted to look at from livestock sales induced by economic shocks and weather shocks that the sampled households faced. To do so, the reference period was set as the first four months, from November 2012 to February 2013; during this period, the livestock transaction amounts were calculated. In addition to livestock sales and purchases, the amounts of livestock given and received as gifts were also taken into consideration, as such endogenous transactions can also be affected by weather insurance. To aggregate the transaction amounts of several animals into a single index, we assigned to each animal weights based on livestock prices.[33] Using those weights, the net transaction amounts were calculated for large and small livestock. Note that a positive value in these newly constructed variables referred to "sales," or a reduction in the relevant category of livestock.

These variables were regressed on the same explanatory variables as before (Table 14). As can be seen in column (1) of Table 14, the effects on small-livestock transactions are marginally significant, while the effects on large-livestock transactions are insignificant. The *p*-values of the estimated coefficient on total insurance payout in the small-livestock transactions regression range from 0.09 to 0.11, depending on the bootstrap resampling. Thus, small-livestock holdings might have been crowded out by the introduced insurance contract, and farmers could have considered the weather index insurance a substitute. However, the effects were minimal: a ZMW80 increase in insurance payout would induce farmers to give up approximately a 0.1 pig-equivalent unit—an amount exactly equal to one chicken. The average price of one chicken was about ZMW20, which suggests that weather index insurance might not be cost-effective for local farmers in mitigating risk. Since the weather index insurance corresponded only to rainfall failure and it did not mitigate other important types of risk—such as household illness—small-livestock holdings would have been recognized as a more flexible way of coping with the risk that local farmers face, compared to weather index insurance. Because the insurance payout provided by the project might have been relatively smaller than their demand for precautionary saving, only weather index insurance did not suffice, at least in terms of their existing self-finance strategy, in producing complete compensation. Along with the reported evidence that the uptake of insurance leads to agricultural investments in many dimensions, our tentative interpretation is that insured farmers might source the money needed to fund agricultural inputs by making small-livestock transactions. While the empirical results that

[33] For large livestock, we assigned the value of 1 to oxen, 0.75 to cows, and 0.3 to calves. For small livestock, we assigned the value of 1 to pigs, 0.5 to each of piglets and adult goats, 0.25 to child goats, and 0.1 to chickens.

we obtained support the crowding-out hypothesis with respect to precautionary saving, further research is required if we are to derive a more robust conclusion on this important matter.

6. Robustness check

One may have concerns about our use of the amount of winnings as a preferred IV, as that variable is also reflected in a farmer's selection based on his or her risk preferences. Although we find that risk preferences do not have a statistically significant impact on insurance demand, the exclusion restriction assumption could be violated on account of endogenous risk preferences. To address this concern, we include the amount of winnings as control variables, rather than as an IV, and execute the same exercise with the October 2012 sample dummy as only one IV. We obtained the qualitatively same result as before, with smaller-magnitude coefficients (omitted for space in this version).

Another potential concern might be some of the imbalances in baseline characteristics. Especially, we needed to pay particular attention to family labor inputs—one of our main outcome variables. To address this issue, we added the baseline values of the outcome variable to the vector of the controls, and then run the same regressions as the previous specification at the household level. This approach generated more efficient estimates and minimized potential biases than either relying solely on the endline values of the outcome or a difference-in-difference estimator, even if the difference in baseline outcomes was not statistically significant (Kerwin 2014).

Using the baseline values of the outcome variables as additional controls, Appendix Table 2 replicates Table 13. All the regression results shown in Appendix Table 2 report the qualitatively same results as those in Table 13. Since the coefficient on the baseline value of family labor inputs is not statistically significant in column (8), we exclude from the sample households with an extreme variable of that baseline value. This estimation result based on a limited sample is reported in column (9). As can be seen, the robust effect of the insurance contracts on family labor inputs is confirmed. Overall, we conclude that the estimation results in Section 5 are fairly robust to the several specifications outlined in this section.

7. Conclusions

By exploiting both exogenous variations in endogenous insurance demand and random variations in free insurance, this study presents empirical evidence of the impacts of policy interventions that intend to mitigate weather risk on the agricultural decision-making of small-scale farmers in Zambia. The results reveal that insured farmers expand the amount of land dedicated to maize production, and also increase fertilizer application and family labor inputs. While fertilizer application and hired labor inputs did not change significantly at the intensive margin, the impacts of insurance on changes in family labor inputs at the intensive margin were statistically and economically significant. This finding suggests that the intensification of family labor inputs, compared to that of fertilizer application, is a more feasible strategy for local farmers in Zambia in enhancing agricultural profits.

Liquidity constraints might hinder farmers from investing further in fertilizer and hired labor inputs. Another possibility could be that the marginal profits from increases in family labor inputs were higher than those from increases in fertilizer and hired labor inputs, given the size of the farmers' maize plots. Further investigation would be desirable to determine which explanation is more convincing for this particular study site. In addition, farmers' land-expansion responses to formal weather insurance could be unique to our setting, where agricultural land is fairly abundant and the population density is quite low. Using experimental data from rural Ghana, Karlan et al. (2014) report the same findings on the impacts of rainfall index insurance on land operation size. However, different behavioral responses could be observed in areas with high levels of population pressure, as in South Asian countries. In fact, Cole et al. (2014) report that while insured farmers increase their production of cash crops, insurance has little effect on total agricultural investments by farmers in India, including the expansion of total operation land size.

Another important lesson drawn from this study is that weather index insurance used to compensate for the costs of agricultural inputs in early-stage production can help farmers invest in profitable agricultural technologies. Especially, we observed favorable impacts on the timing of maize seed planting: insured farmers planted maize seeds five days earlier, on average. In the absence of effective insurance markets, farmers can diversify the timing of planting across plots in order to diversify rainfall risks. Because this strategy prevents farmers from choosing an optimal sowing date by which to maximize their expected maize production profits, local farmers will likely forgo agricultural income on account of uninsured weather risk. From the viewpoint of policy by which to enhance agricultural productivity, empowering farmers to plant maize on the optimal sowing date by mitigating weather risk is desirable.

Associations between existing self-insurance and formal insurance were also empirically explored in this study. We found that households with more small livestock tended to have a higher demand for the introduced weather insurance, and that insured farmers tended to reduce the number of their small-livestock holdings upon taking up insurance. In combining these findings, we could conclude that weather index insurance was considered by the farmers a substitute for traditional precautionary savings. We propose a tentative interpretation that insured farmers transact small livestock to source the money for agricultural input purchases. These interesting findings might be suggestive at most, given the small magnitude of the impacts. However, this study is one of the first attempts to provide answers to important questions regarding the relationship between conventional self-insurance mechanisms and new formal insurance.

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Table 1. Subjective perceptions about drought

Variables	Obs.	Mean	Std. dev.	Min.	Max.
Expected maize yield in normal year (kg/ha)	159	1460	895	200	7,200
Expected maize yield in drought year (kg/ha)	159	483	352	0	2,400
How many years do you experience drought, of 10 years?	150	3.02	1.22	0	7

Source: October 2012 household surveys; 160 households in total were surveyed, but there were some missing values.

Table 2. Impacts of rainfall on maize yield in the Choma and Sinazongwe Districts, 1975/76–2010/11

	(1)	(2)	(3)	Summary Statistics
Total rainfall/100 mm	1.3103**			7.61
	[0.5134]			(2.02)
(Total rainfall/100 mm)^2	-0.0797**			
	[0.0354]			
December rainfall/100 mm		1.0131**		1.77
		[0.4102]		(0.91)
(December rainfall/100 mm)^2		-0.2321***		
		[0.0814]		
Flowering season rainfall/100 mm		0.9171**		3.53
		[0.3532]		(1.27)
(Flowering season rainfall/100 mm)^2		-0.0967**		
		[0.0438]		
"Flood"			-0.9729**	0.10
			[0.3905]	dummy
"Drought"			-0.8435***	0.35
			[0.2177]	dummy
Choma	0.7528***	0.8190***	0.7686***	0.69
	[0.2074]	[0.1968]	[0.2042]	dummy
Linear time trend (1975 = 0)	-0.0449***	-0.0442***	-0.0481***	20.33
	[0.0139]	[0.0157]	[0.0122]	(10.31)
Constant	-3.1151*	-0.8962	2.3671***	
	[1.7382]	[0.6615]	[0.3946]	
R-squared	0.47	0.51	0.55	
F-statistics for zero slopes	12.00***	9.08***	16.05***	
Mean of dependent variables		1.52		
Std. dev. of dependent variables		1.04		
No. of observations		51		

Notes: The dependent variable is maize yield (tonnes/ha). The sample covered the period between 1975/76 and 2010/11, with missing observations. The data sources were Crop Forecast Survey Data from the Central Statistical Office (CSO) and Rainfall Data of Choma from the Choma Meteorological Station of the Zambia Meteorological Department (Mochipapa). "Flood" is a dummy that took the value of 1 if the total rainfall amount in December was above 300 mm, and 0 otherwise. "Drought" is a dummy that took the value of 1 if the total rainfall amount during January and February was below 280 mm, and 0 otherwise. The "Summary statistics" column shows means, and standard deviations are in parentheses. In pooling maize yield data from the Choma and Sinazongwe Districts, OLS was used for the estimations. Heteroskedasticity-robust standard errors are in squared brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3. Frequency of “drought” and “flood,” 1975/76–2010/11

	“Drought” year		“Flood” year		
Periods	Frequency	%	Frequency	%	No. of observations
1975/76–2010/11	13	36%	4	11%	36
1981/82–2010/11	9	30%	1	3%	30
2001/02–2010/11	3	30%	1	10%	10

Notes: “Drought” year is defined as an agricultural year whose total rainfall during the flowering season (January and February) is below 280mm. “Flood” year is defined as an agricultural year whose total rainfall in December exceeds 300mm.

Source: Rainfall Data of Choma from the Choma Meteorological Station of Zambia Meteorological Department (Mochipapa).

Table 4. Free insurance money

Groups	Sum of numbers shown on dice	Additional free insurance money	No. of households	
			Insurance sales (October 2012)	Follow-up survey (June 2013)
Treatment group 1	2, 3, 10, 11, 12	ZMW75	45	43
Treatment group 2	4, 7	ZMW50	46	45
Treatment group 3	5, 6	ZMW25	28	27
Control group 1	8, 9	ZMW0	41	39
Control group 2	Control	ZMW0	-	55

Table 5. Baseline descriptive statistics and orthogonality tests

Covariates	(1) Treatment 1 (ZMW75)	(2) Treatment 2 (ZMW50)	(3) Treatment 3 (ZMW25)	(4) Control 1 (ZMW0)	(5) Control 2 (ZMW0)	(6) F-test from regression of var. on each group dummy (*p*-value)
Age of household head	42.9	39.1	47.0	47.2	44.6	1.66
	[15.3]	[13.6]	[16.9]	[15.4]	[17.0]	(0.16)
Education year of household head	5.2	5.9	4.3	4.9	5.4	1.06
	[3.9]	[2.8]	[2.8]	[3.3]	[3.8]	(0.38)
Family size	6.1	7.3	6.6	7.3	5.5	2.42*
	[2.8]	[3.9]	[4.1]	[3.1]	[3.2]	(0.05)
Monthly expenditure	1.09	0.86	0.89	0.93	0.83	0.74
(ZMW1,000)	[1.12]	[0.35]	[0.91]	[0.50]	[0.68]	(0.57)
Cattle	5.79	4.31	3.26	6.51	3.26	2.00
(ZMW1,000)	[7.66]	[4.78]	[7.68]	[7.97]	[4.47]	(0.10)
Small livestock	0.81	0.62	0.54	0.70	0.57	0.64
(ZMW1,000)	[0.90]	[0.68]	[1.10]	[0.80]	[0.73]	(0.63)
Physical assets	1.79	1.77	1.47	2.80	1.93	0.64
(ZMW1,000)	[1.97]	[1.72]	[2.71]	[6.05]	[3.76]	(0.64)
Total land (ha)	3.18	3.85	3.22	3.81	2.41	1.27
	[3.17]	[4.32]	[3.88]	[4.61]	[1.90]	(0.28)
Cultivated land (ha)	1.96	2.21	1.97	2.21	1.69	0.78
	[1.61]	[1.50]	[1.41]	[2.33]	[1.35]	(0.54)
Applied D Compound	37	43	30	61	53	0.68
(kg)	[65]	[67]	[75]	[112]	[94]	(0.61)
Applied urea	65	53	39	76	56	0.81
(kg)	[86]	[63]	[76]	[110]	[85]	(0.52)
Family labor	345	428	342	260	257	2.14*
(man*day)	[263]	[439]	[381]	[182]	[279]	(0.08)
Hired labor	0.16	0.10	0.07	0.04	0.07	1.36
(ZMW1,000)	[0.36]	[0.31]	[0.15]	[0.07]	[0.16]	(0.25)
Maize harvest	1435	1571	1498	1618	1249	0.40
(kg)	[1,599]	[1,730]	[2,329]	[1,182]	[1,132]	(0.81)
F-test from regression of each group dummy	1.22	1.52	0.75	1.28	1.30	

on all above covariates (*p*-value)	(0.27)	(0.11)	(0.73)	(0.22)	(0.21)
	37	42	24	35	55

Notes: One observation in treatment group 3 that took an extreme value in family labor was excluded. The data source was the July 2012 village census. Columns (1)–(5) show the means, and standard deviations are in brackets. *p*-values of F-test in parentheses. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 6. Result of Binswanger-style lottery

Options	Heads	Tails	Expected Returns	Devia-tions	ΔE / Δrisk	No. of respondents choosing the option		Insurance demand (units)	
								Mean	Std. dev.
a	ZMW5	ZMW5	5	0	1	18	11%	1.83	1.04
b	ZMW4	ZMW12	8	4	0.75	42	26%	2.00	0.99
c	ZMW3	ZMW16	9.5	6.5	0.6	24	15%	2.67	2.22
d	ZMW2	ZMW19	10.5	8.5	0.5	30	19%	2.27	1.91
e	ZMW1	ZMW21	11	10	0.33	21	13%	2.52	2.23
f	ZMW0	ZMW22	11	11	0	25	16%	3.00	2.71

Source: October 2012 household survey.

Table 7. Level of understanding: insurance contracts and arithmetic calculations

Questions		Proportion providing correct answer (%)	Mean (std. dev.) of insurance demand (units)		t-test of mean difference (p-value)
			Correct	Incorrect	
Understanding of the insurance contract					
IQ1	Does the insurance pay on the basis of rainfall records at your fields? [Ans: No]	78.1%	2.44 (1.97) n = 125	2.06 (1.64) n = 35	0.25
IQ2	If you buy the insurance, will you get an insurance payout every time? [Ans: No]	80.0%	2.48 (2.03) n = 128	1.84 (1.17) n = 32	0.02
IQ3	Assume that it rains 250 mm at the Choma weather station in the flowering period (January and February). Will you get an insurance payout? [Ans: Yes]	70.0%	2.57 (2.13) n = 112	1.85 (1.09) n = 48	0.01
IQ4	Assume that it rains 350 mm at the Choma weather station in December. Will you get an insurance payout? [Ans: Yes]	76.3%	2.49 (2.07) n = 122	1.92 (1.12) n = 38	0.03
IQ5	Assume that you experience crop failure due to drought during the flowering period and it rains 300 mm at the Choma weather station during this period. Will you get an insurance payout? [Ans: No]	66.3%	2.55 (2.19) n = 106	1.98 (1.09) n = 54	0.03
Understanding of the arithmetic involved					
MQ1	3 + 6? [Ans: 9]	85.6%	2.53 (1.98) n = 137	1.35 (0.83) n = 23	0.00
MQ2	43 + 86? [Ans: 129]	53.1%	2.79 (2.23) n = 85	1.87 (1.30) n = 75	0.00
MQ3	4 × 8? [Ans: 32]	54.4%	2.84 (2.28) n = 87	1.78 (1.08) n = 73	0.00

Notes: Standard deviations are in parentheses. *t*-tests for mean differences were conducted under an assumption that allowed for the unequal variance of two groups.

Source: October 2012 household survey.

Table 8. Subjective perceptions of rainfall risk

	Site A (55 households)		Site B (49 households)		Site C (56 households)		F-statistics for
	Mean	Std. dev.	Mean	Std. dev.	Mean	Std. dev.	equal means
“Drought”	2.98	1.38	2.78	1.36	2.95	1.57	$F(2, 157) = 0.30$
“Normal”	4.25	1.36	4.76	1.48	4.55	1.32	$F(2, 157) = 1.73$
“Flood”	2.76	1.20	2.47	1.24	2.50	1.14	$F(2, 157) = 0.99$

Source: October 2012 household survey.

Table 9. Determinants of demand for weather index insurance

	Purchased units of insurance contracts			Dummy (=1 if purchased more than 3 units)			
	OLS	OLS	OLS	Probit	Probit	Probit	Summary
	(1)	(2)	(3)	(4)	(5)	(6)	statistics
Sample in 2011	0.2394	0.1352	0.1577	0.1384**	0.1113	0.1165*	0.40
	[0.4624]	[0.4718]	[0.4593]	[0.0699]	[0.0679]	[0.0684]	dummy
Elicited risk preference	-1.1475**		-0.6610	-0.0832		-0.0326	0.54
	[0.5462]		[0.5471]	[0.0653]		[0.0659]	(0.30)
Winnings (ZMW10)		0.5339***	0.4092**		0.0481**	0.0421	1.13
		[0.1916]	[0.1945]		[0.0244]	[0.0258]	(0.79)
Subjective expectation of	-0.1243	-0.1098	-0.1110	-0.0135	-0.0118	-0.0110	5.49
normal year	[0.1367]	[0.1341]	[0.1325]	[0.0150]	[0.0139]	[0.0142]	(1.39)
=1 if	-0.4914	-0.5628*	-0.5463	-0.0471	-0.0418	-0.0443	0.20
formal forecast used	[0.3489]	[0.3394]	[0.3418]	[0.0364]	[0.0345]	[0.0338]	dummy
=1 if	-0.0196	-0.0132	-0.0076	0.0765*	0.0765*	0.0768*	0.58
traditional forecast used	[0.2840]	[0.2790]	[0.2773]	[0.0432]	[0.0416]	[0.0418]	dummy
=1 if	0.8581**	0.8776**	0.8852**	0.0984**	0.0985**	0.0999**	0.66
have relatives in Choma	[0.3563]	[0.3573]	[0.3536]	[0.0430]	[0.0416]	[0.0416]	dummy
Understanding level of	0.3578**	0.3366**	0.3500**	0.0314	0.0270	0.0275	3.71
insurance contract	[0.1604]	[0.1524]	[0.1565]	[0.0237]	[0.0228]	[0.0230]	(1.06)
Arithmetic skills	0.3195**	0.3158**	0.3067**	0.0450*	0.0436*	0.0429*	1.93
	[0.1295]	[0.1223]	[0.1241]	[0.0256]	[0.0248]	[0.0251]	(1.13)
Value of assets and cattle	0.0086	0.0152	0.0143	-0.0025	-0.0008	-0.0009	5.92
(ZMW1,000)	[0.0265]	[0.0287]	[0.0282]	[0.0034]	[0.0029]	[0.0030]	(9.52)
Value of small livestock	0.8466***	0.7964***	0.8154***	0.1125*	0.1090*	0.1100*	0.71
(ZMW1,000)	[0.2809]	[0.2818]	[0.2875]	[0.0672]	[0.0644]	[0.0648]	(1.00)
Value of small livestock	-0.1269***	-0.1270***	-0.1283***	-0.0244	-0.0276	-0.0273	
^2	[0.0384]	[0.0388]	[0.0392]	[0.0184]	[0.0182]	[0.0185]	
No. of people can be	-0.2723	-0.3253*	-0.3230*	0.0407	0.0410	0.0402	3.87
called on in times of need	[0.1714]	[0.1777]	[0.1723]	[0.0298]	[0.0277]	[0.0283]	(2.71)
No. of people can be called	0.0156	0.0197	0.0193	-0.0049	-0.0052*	-0.0052*	
on in times of need^2	[0.0125]	[0.0133]	[0.0128]	[0.0030]	[0.0028]	[0.0028]	
=1 if Group 2	0.0440	0.0256	0.0174	-0.0143	-0.0221	-0.0204	0.36
	[0.5473]	[0.5537]	[0.5492]	[0.0582]	[0.0558]	[0.0564]	dummy
=1 if Group 3	-0.2631	-0.3982	-0.3488	0.0113	0.0001	0.0042	0.37
	[0.5221]	[0.5387]	[0.5243]	[0.0628]	[0.0597]	[0.0606]	dummy
=1 if household head male	-0.1053	0.1308	0.0391	0.0055	0.0083	0.0031	0.89

	[0.2901]	[0.2935]	[0.2858]	[0.0794]	[0.0654]	[0.0691]	dummy
Age of household head	0.0119	0.0083	0.0089	-0.0013	-0.0015	-0.0015	43.03
	[0.0095]	[0.0090]	[0.0091]	[0.0016]	[0.0016]	[0.0016]	(15.36)
No. of family males	0.0269	-0.0143	-0.0018	0.0100	0.0039	0.0052	1.84
	[0.1427]	[0.1378]	[0.1385]	[0.0192]	[0.0183]	[0.0184]	(1.29)
No. of family females	-0.2262	-0.1732	-0.1984	-0.0142	-0.0098	-0.0111	1.97
	[0.1444]	[0.1318]	[0.1388]	[0.0172]	[0.0161]	[0.0166]	(1.37)
No. of family children	0.1336**	0.1305**	0.1328**	0.0183*	0.0172*	0.0174*	3.15
	[0.0654]	[0.0635]	[0.0633]	[0.0102]	[0.0096]	[0.0097]	(2.14)
=1 if Site A	-0.1946	-0.0735	-0.0755	-0.0305	-0.0201	-0.0201	0.34
	[0.4201]	[0.4497]	[0.4431]	[0.0475]	[0.0476]	[0.0479]	dummy
=1 if Site B	-0.1607	-0.0995	-0.1095	-0.0050	-0.0038	-0.0039	0.31
	[0.3640]	[0.3558]	[0.3622]	[0.0474]	[0.0452]	[0.0456]	dummy
Constant	1.1572	0.0219	0.5260				
	[1.0157]	[0.9426]	[1.0928]				
F-statistics for zero slopes	F(22, 137) = 2.60***	F(22, 137) = 2.90***	F(23, 136) = 2.86***				
Chi-square statistics for zero slopes				$\chi^2(22) =$ 57.38***	$\chi^2(22) =$ 54.78***	$\chi^2(23) =$ 56.29***	
Mean of dep. var.		2.36			0.19		
Std. dev. of dep. var.		1.90			dummy		
No. of observations	160	160	160	160	160	160	

Notes: In columns (4)–(6), marginal probabilities are reported. The columns of summary statistics show means, and standard deviations are in parentheses. Heteroskedasticity-robust standard errors are in brackets. * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 10. First-stage regression: endogenous insurance demand

	(1) Plot level	(2) Household level
Insurance sales sample dummy	29.5325***	25.3711***
	[3.6991]	[3.7615]
Winnings	4.8145**	6.1304*
	[2.4230]	[3.1421]
Household characteristics	YES	YES
Land characteristics	YES	-
Village dummies	YES	YES
R-squared	0.55	0.49
F-test for the two IVs	65.63***	77.45***
F-statistics for zero slopes	7.76***	12.68***
No. of observations	379	193

Notes: The dependent variable is the insurance payout on insurance contracts purchased by household. The summary statistics of the dependent variables are: 28.30 (average) and 29.78 (standard deviation) in column (1), and 26.74 (average) and 30.13 (standard deviation) in column (2). Household characteristics included the following 13 variables: gender of household head, age of household head, education years of household head, dummy for having relatives in Choma, number of male adults, number of female adults, number of family children, value of large livestock, value of physical assets holdings, value of small livestock and its squared term, and the number of people who could be called on in times of need and its squared term. Land characteristics included the following eight variables: four indicators for topographical position, total land size, distance to plot from home in minutes, and two indicators for self-reported soil quality. While robust standard errors clustered by household are in brackets in column (1), heteroskedasticity-robust standard errors are in brackets in column (2). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 11. Impacts of insurance contracts on agricultural investments in risky inputs (plot level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Land area cultivated	New seed	Early-maturity seeds	Timing of planting	D Compound	Urea	Family labor	Hired labor
	OLS	Probit	Probit	OLS	Tobit	Tobit	OLS	Tobit
Panel A: Endogenous regression								
Total insurance payout	0.0023**	0.0015*	0.0012	-0.0490**	0.0998	0.1782**	0.3311***	-0.0541
	[0.0009]	[0.0009]	[0.0007]	[0.0231]	[0.0865]	[0.0728]	[0.1166]	[0.3062]
Panel B: Control function approach								
Total insurance payout	0.0013**	0.0038	0.0033	-0.0599**	0.0886	0.1213*	0.3204***	-0.0653
	[0.0006]	[0.0025]	[0.0020]	[0.0249]	[0.0986]	[0.0735]	[0.0987]	[0.2929]
Residual from first stage	0.0048**	0.0008	-0.0008	0.0541	0.0548	0.2551	0.0529	0.0844
	[0.0022]	[0.0067]	[0.0045]	[0.0477]	[0.2044]	[0.1856]	[0.2000]	[0.6179]
Household characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Land characteristics	YES	YES	YES	YES	YES	YES	YES	YES
Village dummies	YES	YES	YES	YES	YES	YES	YES	YES
Unit of outcome variables	ha	dummy	dummy	days	kg	kg	Person-days	ZMW
Mean of outcome variables	0.80	0.53	0.40	34.70	22.08	27.89	89.39	29.76
Std. dev. of outcome variables	0.73	dummy	dummy	18.97	35.44	40.39	71.98	78.76
Frequency of 0	0	177	227	2	222	181	0	266
No. of observations	379	379	378	379	377	377	378	378

Notes: For Panel A, robust standard errors clustered by household are in brackets. For Panel B, the standard errors clustered by household are in brackets and were obtained from 1,000 bootstrap iterations. Summary statistics of total insurance payout: 57.32 (average) and 46.70 (standard deviation) (n = 379). * p < 0.1, ** p < 0.05, *** p < 0.01.

Table 12. Impacts of insurance contracts on agricultural investments in risky inputs per cultivated area (plot level)

	(1)	(2)	(3)	(4)
	D Compound	Urea	Family labor	Hired labor
	Tobit	Tobit	OLS	Tobit
Panel A: Endogenous regression				
Total insurance payout	0.1423	0.0725	0.5769*	-0.3542
	[0.1289]	[0.1048]	[0.3043]	[0.6057]
Panel B: Control function approach				
Total insurance payout	0.1191	0.0480	0.6896***	-0.4345
	[0.1381]	[0.1126]	[0.2365]	[0.5533]
Residual from first stage	0.1155	0.1190	-0.5577	0.6826
	[0.2509]	[0.2215]	[0.5144]	[1.1095]
Household characteristics	YES	YES	YES	YES
Land characteristics	YES	YES	YES	YES
Village dummies	YES	YES	YES	YES
Unit of outcome variables	kg/ha	kg/ha	Person-days/ha	ZMW/ha
Mean of outcome variables	30.34	39.22	165.94	47.79
Std. dev. of outcome variables	47.28	55.70	204.07	143.50
Frequency of 0	222	181	0	266
No. of observations	377	377	378	378

Notes: For Panel A, robust standard errors clustered by household are in brackets. For Panel B, the standard errors clustered by household are in brackets and were obtained from 1,000 bootstrap iterations. Refer to the footnote in Table 10 for household and land characteristics. Summary statistics of total insurance payout: 57.32 (average) and 46.70 (standard deviation) (n = 379). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 13. Impacts of insurance contracts on agricultural investments in risky inputs (household level)

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Size of operated land	Size of operated maize land	D Compound	Urea	Fertilizer	Family labor	Hired labor
	OLS	OLS	Tobit	Tobit	Tobit	OLS	Tobit
Panel A: Endogenous regression							
Total insurance payout	0.0061**	0.0055*	0.2418	0.2730*	0.4517**	0.6448**	0.6414
	[0.0028]	[0.0028]	[0.1496]	[0.1494]	[0.2213]	[0.2885]	[0.6538]
Panel B: Control function approach							
Total insurance payout	0.0041*	0.0035*	0.2351	0.1683	0.3419	0.7685**	0.2490
	[0.0022]	[0.0019]	[0.1940]	[0.1643]	[0.2699]	[0.3784]	[0.8241]
Residual from first stage	0.0085	0.0088	0.0271	0.4202	0.4438	-0.5360	1.7393
	[0.0090]	[0.0094]	[0.4050]	[0.4089]	[0.6033]	[0.7219]	[1.5838]
Household characteristics	YES	YES	YES	YES	YES	YES	YES
Village dummies	YES	YES	YES	YES	YES	YES	YES
Unit of outcome variables	ha	ha	kg	kg	kg	Person-days	ZMW
Mean of outcome variables	1.91	1.56	44.25	56.62	100.87	220.03	103.32
Std. dev. of outcome variables	1.45	1.34	67.29	86.31	138.55	188.37	316.19
Frequency of 0	1	4	99	85	78	1	111
No. of observations	193	193	193	193	193	193	193

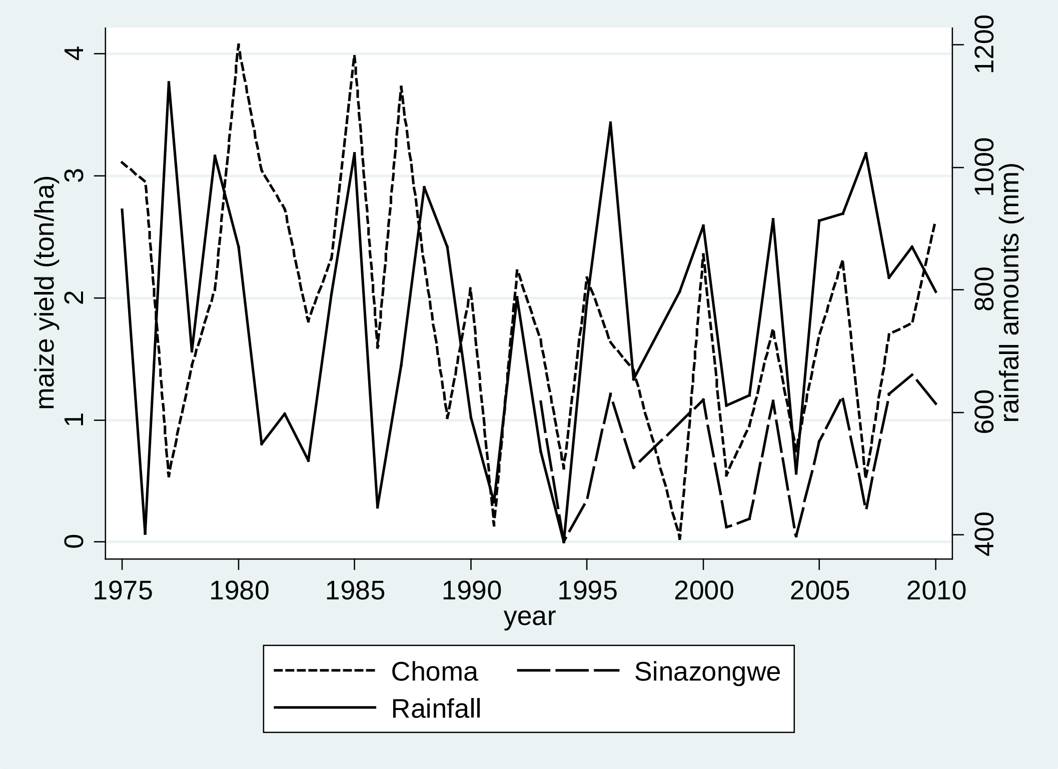
Notes: For Panel A, heteroskedasticity-robust standard errors are in brackets. For Panel B, the robust standard errors are in brackets and were obtained from 1,000 bootstrap iterations. Refer to the footnote in Table 10 for household characteristics. The dependent variable in column (5) is the total amounts of applied D Compound and urea, in kg. Summary statistics of total insurance payout: 55.10 (average) and 47.82 (standard deviation) (n = 193). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 14. Impacts of insurance contracts on livestock transactions

	(1) Small-livestock net transactions OLS	(2) Large-livestock net transactions OLS
Panel A: Endogenous regression		
Total insurance payout	0.0011*	0.0003
	[0.0006]	[0.0004]
Panel B: Control function approach		
Total insurance payout	0.0012	-0.0001
	[0.0008]	[0.0004]
Residual from first stage	-0.0007	0.0019
	[0.0016]	[0.0013]
Household characteristics	YES	YES
Village dummies	YES	YES
Mean of outcome variables	0.09	0.04
Std. dev. of outcome variables	0.45	0.27
No. of observations	193	193

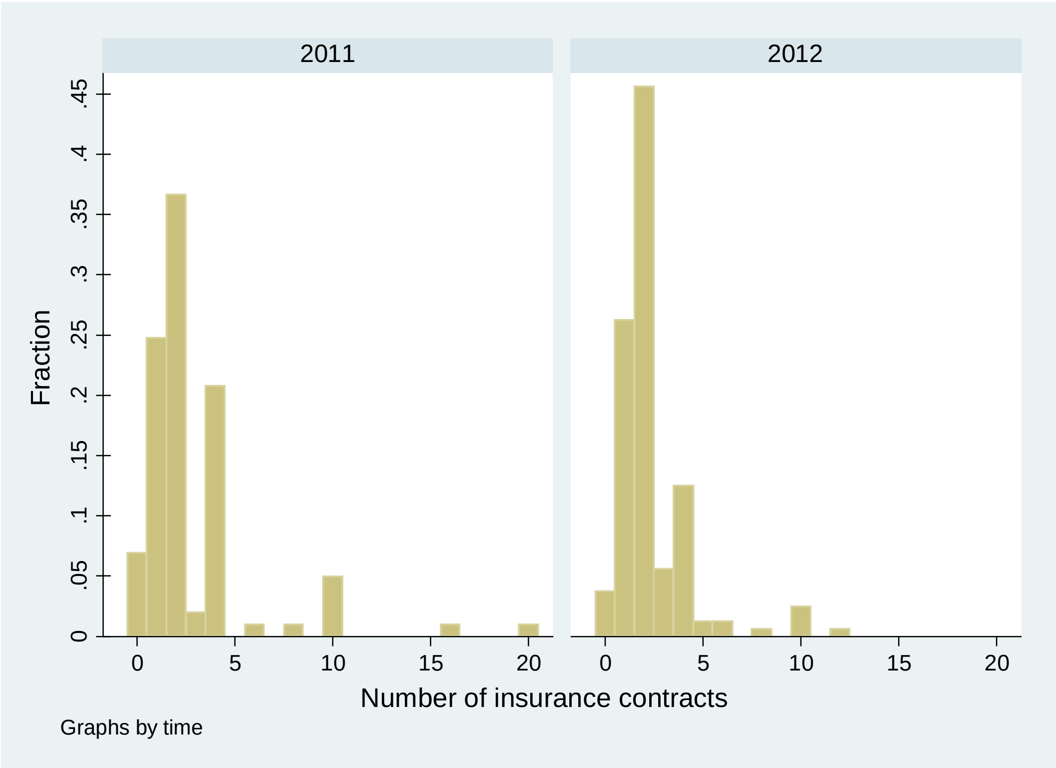
Notes: For Panel A, heteroskedasticity-robust standard errors are in brackets. For Panel B, the robust standard errors are in brackets and were obtained from 1,000 bootstrap iterations. Refer to the footnote in Table 10 for household characteristics. The summary statistic of total insurance payout: 55.10 (average) and 47.82 (standard deviation) (n = 193). * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Figure 1. Rainfall and maize yields in the
Choma and Sinazongwe Districts, 1975/76–2010/11



Source: Crop Forecast Survey Data by the Central Statistical Office (CSO), and Rainfall Data of Choma by the Choma Meteorological Station of Zambia Meteorological Department (Mochipapa).

Figure 2. Insurance uptake in 2011 and 2012



Note: The number of observations was 101 for the 2011/12 agricultural season and 160 for the 2012/13 agricultural season.

Source: November 2011 and October 2012 household surveys.

Appendix Table 1. Impacts of rainfall on maize yield in the Choma and Sinazongwe Districts, 1990/91–2010/11

	(1)	(2)	(3)	Summary statistics
Total rainfall/100 mm	1.0791**			7.58
	[0.4179]			(1.93)
(Total rainfall/100 mm)^2	-0.0612**			
	[0.0282]			
December rainfall/100 mm		1.3724***		1.69
		[0.3911]		(0.83)
(December rainfall/100 mm)^2		-0.3000***		
		[0.0703]		
Flowering season rainfall/100 mm		1.7632***		3.54
		[0.2599]		(1.07)
(Flowering season rainfall /100 mm)^2		-0.2230***		
		[0.0372]		
"Flood"			-1.0501***	0.06
			[0.2171]	dummy
"Drought"			-0.7701***	0.33
			[0.2028]	dummy
Choma	0.6970***	0.7228***	0.7232***	0.56
	[0.1941]	[0.1661]	[0.1754]	dummy
Linear time trend (1975 = 0)	-0.0164	-0.0143	0.0047	25.89
	[0.0198]	[0.0146]	[0.0182]	(5.99)
Constant	-3.2671**	-3.3520***	0.9292*	
	[1.2589]	[0.5597]	[0.5374]	
R-squared	0.47	0.68	0.52	
F-statistics for nonzero slopes	7.85***	18.18***	9.36***	
Mean of dependent variables		1.14		
Std. dev. of dependent variables		0.76		
No. of observations		36		

Notes: The dependent variable was maize yields (tonnes/ha). The sample covered the period between 1990/91 and 2010/11, with missing observations. The data sources were Crop Forecast Survey Data from the Central Statistical Office (CSO) and Rainfall Data of Choma from the Choma Meteorological Station of the Zambia Meteorological Department (Mochipapa). "Flood" is a dummy that took the value of 1 if the total rainfall amount in December was above 300 mm, and 0 otherwise. "Drought" is a dummy that took the value of 1 if the total rainfall amount during January and February was below 280 mm, and 0 otherwise. The "Summary statistics" column shows means, and standard deviations are in parentheses. In pooling maize yield data from the Choma and Sinazongwe

Districts, OLS was used for the estimations. Heteroskedasticity-robust standard errors are in brackets. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Appendix Table 2. Impacts of insurance contract on agricultural investment in risky input at household level, controlling for baseline values of outcome variables

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Size of operated land	Size of operated maize land	D Compound	Urea	Fertilizer	Family labor	Family labor	Hired labor
	OLS	OLS	Tobit	Tobit	Tobit	OLS	OLS	Tobit
Total insurance payout	0.0035*	0.0035*	0.2960*	0.1555	0.3658	0.7728**	0.7128*	-0.2178
	[0.0020]	[0.0019]	[0.1670]	[0.1586]	[0.2543]	[0.3898]	[0.3838]	[0.7323]
Residual from first stage	0.0083	0.0076	-0.1731	0.4250	0.2987	-0.5442	-0.9893	2.2462
	[0.0095]	[0.0100]	[0.3480]	[0.3741]	[0.5590]	[0.7260]	[0.7729]	[1.4359]
Baseline values of outcome variables								
Size of operated land	0.3723***							
	[0.0974]							
Size of operated maize land		0.2915**						
		[0.1287]						
D Compound			0.6016***					
			[0.1271]					
Urea				0.2904*				
				[0.1559]				
Fertilizer					0.4323***			
					[0.1226]			
Family labor						-0.0022	0.1247*	
						[0.0587]	[0.0702]	
Hired labor								0.0005*
								[0.0003]
No. of observations	193	193	193	193	193	193	186	193

Notes: The standard errors clustered by household in brackets were obtained from 1,000 bootstrap iterations. The summary statistics of total insurance payout: 57.32 (average) and 46.70 (standard deviation) (n = 379). The same household characteristics and village dummies as those in Table 13 are also included. Refer to the footnote in Table 10 for household characteristics. The dependent variable in column (5) is the total amounts of applied D Compound and urea, in kg. See Table 13 for the summary statistics of each outcome variable. The sample in column (8) is limited to households with fewer than 1,200 man-days in the village census. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.