The Impact of Weather Insurance on Consumption, Investment, and Welfare

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Abstract

Weather variations crucially affect the wellbeing of farmers in developing countries. I develop and estimate a dynamic stochastic optimization model to assess the impact of weather insurance on the consumption, investment, and welfare for farmers in developing countries. The parameters of the model are pinned down with a combination of calibration and structural estimation using data from Malawi. Contrary to some past work, I find that weather insurance has the potential to provide substantial welfare gains equivalent to almost a 17% permanent increase in consumption. These gains can be magnified especially for the poorest households by contemporaneously extending credit to finance the additional desired investment. In an extension of the model I also show that weather insurance can allow for the adoption of riskier but more-productive improved seeds, further boosting farmers’ welfare. Finally, I explore the extent to which the interplay with other uninsured risks, the presence of basis risk, and a loading factor on the insurance premium may lower the welfare gains from weather insurance, and lead to low take-up as is often observed empirically.

Keywords: Weather insurance, credit, welfare, entrepreneurial risk, technology adoption

JEL Classification Codes: G22, O12, O13, O16, O33, Q14

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1 Introduction

Weather variations can have severe effects on the well-being of farmers in developing countries. From the Ethiopian Rural Panel Data Survey, Dercon (2002) finds that 78% of households suffered “hardship episodes” over the past 20 years as a result of harvest failures brought about by weather shocks. Similarly, Cole et al. (2009) report that drought and weather risks in general are identified as the major source of adverse income shocks by almost 88% of Indian rural households in the state of Andhra Pradesh and Gujarat. The fact that farmers’ income strongly depends on weather is also dramatically exemplified by the spike in the suicide rate recently observed after three consecutive years of droughts in Andhra Pradesh.¹

Weather shocks are particularly welfare detrimental because they are difficult to insure against. As shown by Giné, Townsend and Vickery (2007) they are spatially covariant, affecting all households living nearby and thus severely limiting the effectiveness of informal risk-sharing networks. The provision of formal weather insurance therefore has the potential to largely enhance welfare. Based on this premise, a growing proportion of resources has been devoted to the advocacy and promotion of weather insurance projects. Alderman and Haque (2007) and Hess et al. (2005) provide a review of some of the multimillion-dollar weather insurance projects in developing countries, such as Mongolia, Ethiopia, Malawi, Kenya, India, Mexico, Nicaragua, Ukraine, Peru, and, still in a pilot stage, Madagascar and Tanzania. For instance in 2008, AGROASEMEX, a Mexican company that markets insurance against drought, covered about 1.8 million hectares (nearly 4,500,000 acres). The United Nations World Food Programme recently purchased nearly US$ 1 million of weather insurance derivatives for Ethiopian farmers (corresponding to a maximum payout of US$ 7.1 million) from Axa Reinsurance, one of the largest European insurance companies. Analogously, the World Bank has disbursed a loan of US$ 180 million that includes a pilot project for drought safety net (US$ 2.3 million) and a component of technical support to crop-specific insurance (US$ 0.8 million). The Agricultural Insurance Company of India offers protection against excessive and deficit rainfall, humidity and frost for more than 1 million Indian farmers.

Despite the many resources devoted to promote weather insurance, there has been little research to quantify its potential benefits. As recognized by Morduch (2006), “the expanding gaggle of microinsurance advocates are ahead of the available evidence on insurance impacts. ... The advocates may be right, at least in the long term, but it is impossible to point to a broad range of great evidence on which to base that prejudice”. If anything recent research casts doubts about the effectiveness of weather insurance. Rosenzweig and Wolpin (1993) show that the availability of weather insurance has little effect on the well-being of Indian farmers, and recent experimental studies have somewhat surprisingly found a low take-up of weather insurance.²

In this paper, I construct and structurally estimate a dynamic stochastic model of investment


²See for instance the randomized experiments by Cole et al. (2009) in India to understand the determinants of weather insurance take-up, and the work by Giné and Yang (2009) in Malawi.
and consumption for farmers in developing countries. I first quantify the potential welfare gains from the provision of weather insurance in an ideal setting without basis risk and loading factor, where agents are able to observe the realization of the idiosyncratic productivity shock before purchasing weather insurance. I then relax these assumptions and study the extent to which these three factors can limit the potential benefits and lead to a lower take-up consistent with the empirical evidence. In the model, farmers are subject to both idiosyncratic shocks and aggregate weather fluctuations that affect crops yields. The farmers’ only source of income is from agricultural investment. Considering the qualitative implications of the model, I show that the introduction of insurance has a priori uncertain implications for consumption and investment. On the one hand, farmers may want to boost consumption since they face lower income risk. On the other hand, they may desire to invest more since returns have become more stable. Which of these two forces prevails and their ultimate impact on the level of investment depends on the parameters of the model and therefore remains an empirical question.

I proceed to quantify the welfare gains from actuarially-fair-weather insurance by calibrating the empirical distribution of the weather shocks with agronomic data from Malawi, and pinning down the other parameters through a mix of calibration and structural estimation based on the Malawian survey data from Giné and Yang (2009). The potential gains from weather insurance can be quite large, equivalent to a permanent increase of 16.9% of consumption. Exploiting the dynamic structure of the model I also assess how these gains evolve over time. Once weather insurance becomes available, households tend to increase consumption at the cost of reducing the stock of capital for investment, which can lower future income and reduce the welfare gains of subsequent generations. It is interesting to consider that this result is obtained even though I assume full bequest motives so that parents care about their children’s future welfare as much as their own. I then contrast the welfare gains from weather insurance with those derived from the provision of credit and investigate the synergies between the joint supply of credit and insurance. Poorer farmers benefit the most when weather insurance is jointly supplied with credit which allows households to finance the additional desired investment.

I also explore an additional channel that can further increase the gains from weather insurance. By relaxing the exposure to weather risk, it may enable farmers to adopt riskier but more productive investment opportunities thus boosting farm income. To investigate this additional source of gains, I extend the framework of analysis and allow farmers to choose between two production technologies (i.e. planting hybrid or traditional crops) with different expected return/volatility combinations. I find that the provision of weather insurance leads to more investment in the riskier technology, enabling households to contemporaneously increase consumption and farm income. This result has interesting dynamic welfare implications since welfare gains no longer decrease over time as in the case when only one farming technology is available, but instead actually increase.

Despite the large welfare gains that the model has uncovered, empirical experimental studies

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3Similar remarks are made by Angeletos (2007) and Covas (2006) who analyze the effects on aggregate consumption and savings of variations in uninsured idiosyncratic investment risk.
often find little take-up of weather insurance. I investigate the extent to which this can be due to loading factor, basis risk and the interplay with other uninsurable risks.\footnote{Given the structure of the contract I leave aside issues related to moral hazard and adverse selection which are not relevant since payments are conditional on weather realizations directly observed by the insurer through local weather stations.} I find that if the cost of insurance is inflated by a loading factor both welfare gains and the optimal take-up fall proportionally by a significant amount. Similar results are obtained with basis risk, so that insurance payments do not perfectly map to farmers’ losses due to weather variations. Finally, the presence of uninsurable idiosyncratic risk affecting agricultural productivity that is not realized before the purchase of weather insurance may greatly lower take-up but reduces welfare gains only moderately.

The remainder of the paper is organized as follows. After discussing the related literature in Section 2, I outline the theoretical model in Section 3, and show the \textit{a priori} unclear effect on consumption and investment of weather insurance. The data sources for the calibration and estimation of the model are described in Section 4.1, and the estimation strategy is presented in Section 4.2. In Section 5, I quantify the welfare gains from the provision of weather insurance, and analyze how these gains vary over both wealth and time. I also investigate the existence of synergies with the provision of credit for investment and study the sensitivity of the results to alternative parameter values. In Section 6 I investigate how the provision of weather insurance affects farmers who have the opportunity to invest in two crops that differ in terms of productivity and riskiness. Finally, in Section 7 I analyze the impact on welfare gains of including basis risk in the insurance contract, charging a loading factor, and not allowing farmers to observe their idiosyncratic productivity before purchasing weather insurance.

2 Related literature

To the best of my knowledge, Rosenzweig and Wolpin (1993) are the first who tried to assess the welfare gains from the provision of weather insurance to farmers. Using a finite-horizon dynamic model of agricultural investment and the longitudinal Indian household data collected by the International Crops Research Institute for the Semi-Arid-Tropics (ICRISAT), they structurally estimate the impact of alternative welfare policies on Southern Indian farmers. They claim that the introduction of actuarially fair weather insurance is associated with only negligible welfare gains. Conversely, they find that the provision of a fixed and stable additional source of income improves households’ ability to smooth consumption, and thus is substantially welfare enhancing.

The welfare gains from weather insurance in Rosenzweig and Wolpin (1993) are potentially downward biased because of their modeling and estimation strategy. First, the authors assume that even when households are hit by a large negative shock, they are guaranteed a minimum level of consumption. This assumption seems to be required by the structure of the profit shocks, which are normally distributed and enter linearly in the production function. Therefore, to avoid untractable results involving negative income and negative consumption, the authors need to impose a minimum consumption floor. This requirement however has the potential to substantially reduce the need
for insurance, since households are already automatically insured against the worst shocks. I adopt a different formulation of the production function that eliminates the need to impose a minimum consumption floor and allows for decreasing marginal returns. These features may help to quantify more realistically the benefits from weather insurance.

Second, the estimates of the structural parameters may not be sufficiently precise. The authors focus their analysis on understanding the process of accumulation of bullocks, which are considered as both production and saving assets. Since households own a maximum of two oxen and one water pump, Elbers, Gunning and Pan (2007) warn that the low level of heterogeneous variation in the farming inputs data may affect the estimation of the structural parameters. I instead estimate the model considering the overall value of capital invested in the cultivation of crops, bundling the expenditures on irrigation, fertilizer, manure, and other farm inputs. This approach ensures more variation in the data and potentially more precise estimates of the parameters of interest.

Furthermore, I explore an additional channel through which weather insurance can improve welfare that was completely disregarded by Rosenzweig and Wolpin (1993). I extend the analysis to the production of two crops, introducing the possibility for farmers to adopt a more productive but riskier technology. Numerical simulations show that weather insurance significantly improves farmers’ welfare by increasing the take-up of high-risk high-productivity technology.

To estimate the model I use the survey data collected for the randomized experiment conducted in Malawi by Giné and Yang (2009), who analyze how farmers’ investment decisions are affected by liquidity constraints and risk preferences. Specifically, they investigate whether the take-up of hybrid seeds is hindered by lack of liquidity or excessive exposure to production risk, by providing only credit to the control group, and credit plus actuarially-fair weather insurance to the treatment group when selling hybrid seeds. If the lack of liquidity is the key factor, the relaxation of credit constraints should be enough to generate the optimal adoption of hybrid technology. If instead farmers are deterred by the higher riskiness attached to the hybrid seeds, the provision of insurance should play a major role.

Rather surprisingly Giné and Yang (2009) find that the take-up is generally low and higher among the control group: only 20% of the farmers who were offered the package of credit bundled with insurance bought it, whereas 33% bought the credit only product. However, the authors warn not to take this finding as evidence that liquidity constraints are the only relevant element for the investment choice. Given that default is almost costless in rural Malawi, farmers are not willing to pay for the actuarially fair premium since credit already incorporates the insurance component. In this paper, the structural model allows me to quantify the welfare gains from weather insurance and credit by ruling out default and thereby clarifying who benefits and by how much from these two different policies.

\[5\text{Banks are not likely to extend credit to purchase hybrid seeds at affordable rates given the high default rates due to the significant weather risks to which farmers are exposed. The provision of weather insurance would reduce the default risk, thus improving access to credit for farmers who then may be more likely to borrow to finance the purchase of more-productive technology.}\]


3 Model

To characterize the effects on consumption, investment and welfare from the provision of weather insurance, I construct a dynamic model of farmers in developing countries facing aggregate weather risks and idiosyncratic shocks. I first set up the “baseline” framework used to investigate farmers’ optimal consumption and investment decisions in the absence of weather insurance, and contrast it with the model proposed by Rosenzweig and Wolpin (1993). I then introduce weather insurance (the “insurance” framework) and study the qualitative implications of its provision.

3.1 Baseline framework

Each period households decide how much of their resources to consume, $c_t$, and how much to invest in agricultural inputs, $k_t$, from which they earn farm income, $w_{t+1}$, according to a production function with decreasing marginal returns.\(^6\) Farmers maximize the expected present discounted value of consumption $E_t \sum_{j=0}^{\infty} \beta^j u(c_{t+j})$ where $u(c_t) = \frac{c_t^{1-\rho}}{1-\rho}$ is a constant relative risk-aversion (CRRA) utility function with a coefficient of relative risk aversion $\rho$.

In the absence of markets for insurance and credit, the farmers’ optimization problem (the “baseline” framework) can be expressed as follows:

$$V(w_t) = \max_{k_t} [u(c_t) + \beta E_t V(w_{t+1})]$$

$$w_t = c_t + k_t$$

$$w_{t+1} = A_i \epsilon_{i,t} k_t a_i^{\alpha} \eta_{t+1}$$

where $\eta_{t+1}$ is the aggregate weather shock whose realization is unknown to farmers at the time they make investment decisions, $a_i$ is the land owned by each farmer, $A_i$ is the individual-specific time-invariant productivity coefficient, and $\epsilon_{i,t}$ is an idiosyncratic shock to farmers’ productivity, such as illness or pests, farmers observe before allocating resources to either investment, $k_t$, or consumption, $c_t$. The idiosyncratic terms, $A_i$ and $\epsilon_{i,t}$, are both log-normally distributed with mean 1 and variance, respectively, of $\sigma^2_{A_i}$, and $\sigma^2_{\epsilon_i}$. The distribution of the weather shock, $\eta_{t+1}$, is empirically calibrated from the data as discussed in Section 4.1. Land, $a_i$, is not included in the budget constraint and does not have the time subscript, since I assume that farmers cannot adjust the amount of land with which they are endowed.\(^7\)

The first-order condition for the optimal level of capital is computed by equating the marginal

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\(^6\)Throughout the paper, I use the terms “income” and “wealth” interchangeably. Under the “baseline” regime, since neither credit nor savings are allowed, the value of income corresponds to that of wealth. Under all other regimes, the term $w_{t+1}$ indicates the wealth level corresponding to the amount of income available for consumption once insurance and/or debt are paid off.

\(^7\)In developing countries, land trading is often limited by lack of property rights: indeed, according to the survey data from Giné and Yang (2009) farmers claim ownership with deeds on only 25% of the land. Moreover, it is unlikely that farmers would find it profitable to sell their land when struck by an aggregate negative weather shock. Prices of durable goods would fall as neighboring households seek the same coping strategy, i.e. they contemporaneously want to sell land to offset a negative wealth shock.
utility of consumption today to the expected discounted marginal utility of consumption tomorrow:

$$u'(c_t) = \beta E_t[u'(c_{t+1})\alpha_i A_i k_t^{\alpha - 1} a_{i}^{1 - \alpha} \eta_{i,t} + 1]$$ (2)

It is important to note that the model implies a finite target level of wealth toward which farmers will converge. For instance, assuming perfect foresight, it is possible to explicitly solve for the steady state of wealth from equation (2), where households optimize their consumption decisions to equate the marginal product of capital to the intertemporal discount rate, $\alpha k_t^{\alpha - 1} a_{i}^{1 - \alpha} = \frac{1}{\beta}$. When investment risk is accounted for, equation (2) is no longer deterministic, and must be numerically solved. Nevertheless, the same intuition holds so that farmers would scale up their investment until the risk-adjusted marginal return from investment compensates for the discount factor. The target level of wealth thus is generally defined in the literature as the level of wealth in the $t^\text{th}$ period that corresponds to the expected level of wealth in the following period $t^\text{th} + 1$, that is, it is the level of wealth that is expected to be stable.

The model differs from that of Rosenzweig and Wolpin (1993) along several dimensions. First, while they adopt a quadratic function specifying a pump and bullocks as the different farm inputs, I use a Cobb Douglas production function bundling all the different inputs in $k_t$ to obtain more variation in the amount of resources invested, and consequently more precise estimates of the production parameters. Second, unlike in Rosenzweig and Wolpin (1993), shocks enter multiplicatively in the production function and thus do not require imposing a lower bound on consumption to ensure tractability. Finally, I specify an infinite-horizon model to study how weather insurance affects future farmers under a full bequest motive, which differs from Rosenzweig and Wolpin (1993), who use a life-cycle finite-horizon framework.

As in Rosenzweig and Wolpin (1993), I do not account for output price variation caused by weather changes. This paper is based on agronomic data from rural Malawi regarding the production of maize and groundnut, whose prices should not be affected by local weather for two reasons. First, regarding maize production, since the famine in 2002, the Malawian government has imposed an upper bound on the price of maize to ensure that farmers are able to finance consumption even during times of drought. Second, the price of groundnut is determined on international markets where Malawi does not play a significant role and thus domestic weather should not affect the price paid to farmers.

One possible concern is that the modeling framework may overstate the insurance gains since farmers are not allowed to save or earn non-farm income; consequently, they are prevented from using extra funds to sustain consumption when hit by a negative income shock. However, Dercon (1996) observes that in rural Tanzania farmers keep very little savings in cash or deposits because of the double-digit inflation experienced by the country, implying negative rate of returns. In past

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8 As mentioned above, in Rosenzweig and Wolpin (1993) model, farmers own at most one pump and two oxen.

9 Yet there is recent evidence that a negative interest rate does not necessarily discourage savings accumulation. Indeed through a randomized experiment, Dupas and Robinson (2009) have shown that Kenyan farmers deposit their money in no-interest-bearing accounts with substantial withdrawal fees to smooth consumption if hit by a negative health shock.
years, Malawi has indeed experienced high inflation rates reaching their peak at 73% in 2002, and subsequently declining to 18% in 2006, at the time of baseline survey. Consistent with Dercon (1996), I observe that little savings are kept in bank deposits, as shown in Table 2 reporting summary statistics calculated from Giné and Yang (2009) survey data. Indeed savings are mainly in the form of non-liquid assets, and therefore are of limited use to buffer consumption, since, as documented by Dercon (2002), it is unlikely that households could sell these assets and finance consumption when hit by a covariant negative shock, such as a drought. Similarly, as shown in Table 3, non farm income has little effect on consumption smoothing since it comes mainly from wages that agents earn by working on other farmers’ land and thus the wages are likely to fall during a drought.

3.2 Insurance framework

I expand the “baseline” framework to introduce weather insurance by assuming that farmers are offered the opportunity to buy $\iota_{t+1}$ unit(s) of weather insurance. For each unit bought, the insurance contract pays $(1 - \eta_{t+1})$, the amount required to offset any negative weather shock. Farmers’ optimization problem ("insurance" framework) thus becomes

$$V(w_t) = \max_{k_t, c_t \geq 0} [u(c_t) + \beta E_t V(w_{t+1})]$$

$$w_t = c_t + k_t$$

$$w_{t+1} = A_t \iota_{t+1} k_t^\alpha a_t^{1-\alpha} \eta_{t+1} + \iota_{t+1} (1 - \eta_{t+1}) - \iota_{t+1} \mathcal{P}_t$$

where $\mathcal{P}_t$ is the actuarially fair price for one unit of weather insurance and is defined as $\mathcal{P}_t = \int_0^1 (1 - \eta)f(\eta)d\eta$. The term $\mathcal{P}_t$ appears in the transition equation rather than in the budget constraint, since I assume farmers have access to credit to pay for the insurance premium.\footnote{This assumption rules out the possibility that liquidity-constrained farmers may not be able to afford to pay for the premium or would have to forgo consumption or investment to purchase weather insurance.}

As indicated by the timing of the idiosyncratic shock, I assume that farmers are able to observe their level of productivity before purchasing insurance. This assumption combined with the fact that the insurance is actuarially fair ensures that risk-averse farmers want to fully insure, that is $\iota^*_t = A_t \iota_{t+1} k_t^\alpha a_t^{1-\alpha}$.\footnote{In Section 7 I relax these assumptions and show the consequences for the insurance take-up and welfare gains.}

Under full insurance the problem can thus be simply expressed as follows

$$V(w_t) = \max_{k_t} [u(c_t) + \beta E_t V(w_{t+1})]$$

$$w_t = c_t + k_t$$

$$w_{t+1} = A_t \iota_{t+1} k_t^\alpha a_t^{1-\alpha} (\eta_{t+1} + (1 - \eta_{t+1}) - \mathcal{P}_t)$$

Solving the following Euler condition allows us to determine the optimal level of consumption.
and capital for each level of wealth:

\[ u'(c_t) = \beta E_t[u'(c_{t+1})\alpha A_t\epsilon_{t,t}k_t^{a-1}a_t^{1-a}(\eta_{t+1} + (1 - \eta_{t+1}) - P_t)] \tag{5} \]

which states that the marginal utility from an extra unit of consumption today must be equal to the expected marginal value of consumption tomorrow.

It is interesting to note that the introduction of weather insurance does not have a priori a univocal impact on consumption and investment. On the one hand, agents may want to boost investment given its reduced riskiness, but on the other hand they may prefer to consume more and invest less since the precautionary motives to invest are lower. To clarify with an example, Figure 1 traces the evolution of consumption and investment following the introduction of weather insurance under two different calibrations. Depending on the magnitude of the CRRA coefficient, the provision of weather insurance may either increase or decrease investment. Specifically, I calibrate \( \alpha = 0.7, \sigma_{\epsilon} = 0.05, \beta = 0.76, \) and let \( \rho \) be either 0.9 or 2.\(^\text{12}\)

![Impulse response functions](image)

(a) High CRRA coefficient, \( \rho \) is 2

(b) Low CRRA coefficient, \( \rho \) is 0.9

Figure 1: A priori unclear effect of the supply of weather insurance

In the simulations, I assume that households are originally endowed with the target level of wealth under the “baseline” regime. Since they are already at the steady state, the level of consumption and investment remains constant over time until weather insurance is provided (Figure 1). At time \( t^\star \) insurance is unexpectedly and suddenly supplied, inducing agents to modify their

\(^\text{12}\)When plotting the impulse response functions, to capture more precisely the impact on consumption and investment, I set both idiosyncratic and aggregate shocks to their mean values. The actual shocks, however, are obviously present in the calculations of the policy functions.
optimizing behavior. Using the policy functions from the “insurance” framework, households determine the new target level of wealth and the optimal consumption and investment patterns to converge toward it. Figure 1(a) shows that more risk-averse individuals react to the provision of weather insurance by reducing the amount of capital invested given the weakening of precautionary motives. Consequently, consumption jumps upward initially and then declines over time as the level of income falls. Conversely, less risk-averse agents immediately cut consumption to finance additional investment (Figure 1(b)). Their consumption then gradually increases and eventually levels off at a higher level than under the “baseline” regime since farmers achieve higher income due to the initial increase in invested capital.\textsuperscript{13}

4 Calibration and structural estimation

4.1 Data

To calibrate the model and estimate the gains from weather insurance I need to pick appropriate values for the CRRA coefficient $\rho$, the discount factor $\beta$, the capital share $\alpha$, the variance of the idiosyncratic shock $\epsilon_{i,t}$, and the parameters regarding the distribution of the aggregate weather shock $\eta_t$. Note that the production parameters $A_i$ and $a_i$ are exogenously fixed since they act only as scaling factors. As discussed in Section 4.2, their magnitude does not affect the structural estimation of $\alpha$ and $\sigma_\epsilon$ or the calculations of the welfare gains.

I extract information from two different data sources. First, using agronomic data elaborated by the crop water satisfaction analysis (CWSA) module I estimate the empirical distribution of the weather shock $\eta_t$. Second, with Giné and Yang (2009) survey data I calibrate the CRRA coefficient $\rho$, the discount factor $\beta$, and the interest rate on debt $R$ (used to solve for the “credit” and “insurance plus credit” frameworks described in Section 5.1). From the households survey data, I also compute the median level of capital invested $k_t$, and income $w_{t+1}$ which are used to structurally estimate the model’s additional parameters, $\alpha$ and $\sigma_\epsilon$.\textsuperscript{14}

The distribution of the weather shock is derived using agronomic data and the CWSA module, which estimates how weather variations affect farmers’ yields, mapping crops productivity to rainfall times-series data. Specifically, the CWSA module computes the distribution of the crop water index (CWI), which corresponds to the impact on crop production resulting from water deficit.\textsuperscript{15} This can be interpreted as the measure for the weather shock $\eta_t$ since it describes the impact of a water deficit on crop productivity. Figure 2 reports the empirical distribution of the aggregate weather shocks $\eta_{t+1}$ (CWI) which has a mean of 0.69 and variance of 0.04.

To pin down the other model parameters, I use the survey data from Giné and Yang (2009) collected in September 2006. The data are based on the interviews of about 770 maize and ground-

\textsuperscript{13}These findings are in line with the evidence in Covas (2006).

\textsuperscript{14}The Giné and Yang (2009) dataset also contains information regarding the size of any loan ($d_t$) farmers may have active at any point since September 2005; summary statistics are reported in Table 5. There is no information instead regarding farmers’ consumption $c_t$ in the survey data.

\textsuperscript{15}Further details on how the CWSA module is constructed and the data needed to run it are available in Appendix B.
nut farmers from four different regions of central Malawi: Lilongwe North, Mchinji, Kasungu, and Nkhotakota. Farmers were asked a variety of questions regarding their demographic and economic characteristics, ranging from income generating activities to knowledge about financial products.

In particular, I calibrate the coefficient of relative risk aversion $\rho$ and the discount factor $\beta$ using the answers to hypothetical questions regarding the attitude toward risk (the choice of gambles and the timing of lottery payments). The specific questions and the calibration techniques are presented in Appendix B. The interest $R$ used to solve the “credit” and “insurance plus credit” frameworks is set equal to the average interest rate paid by farmers. The values of these parameters are reported in Table 1.

Table 1: Model parameters

<table>
<thead>
<tr>
<th>Distribution of weather shock $\eta_t$</th>
<th>Empirical distribution from the CWSA model</th>
</tr>
</thead>
<tbody>
<tr>
<td>Discount factor $\beta$</td>
<td>0.76 Parameters calibrated</td>
</tr>
<tr>
<td>CRRA coefficient $\rho$</td>
<td>2.67 using Giné and Yang (2009) survey data</td>
</tr>
<tr>
<td>Interest rate on debt $R$</td>
<td>30%</td>
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<tr>
<th>Estimated parameters</th>
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<tr>
<td>Point estimate</td>
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<tr>
<td>Capital share $\alpha$</td>
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<tr>
<td>SD of idiosyncratic shock $\sigma_\epsilon$</td>
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</tbody>
</table>

The remaining parameters $\alpha$ and $\sigma_\epsilon$ are harder to be directly pinned down and therefore, as described in the next section, they are structurally estimated. To do so, data regarding farmers’
wealth and invested capital are needed. As a measure of the former, $k_t$, I consider the total expenditures on farm inputs, calculated as the sum of expenditures on irrigation, fertilizers, chemical pesticides, manure or animal penning, rented equipment (such as tractors), hired manual labor, hired oxen labor, and seeds across each plot farmers cultivate. Table 4 in Appendix C presents the summary statistics for farmers’ total expenditures and the separate components. Farm income, $\mathcal{A}_t \epsilon_{i,t} k_t^{\alpha} a_t^{1-\alpha} \eta_{t+1}$, is calculated as the total revenue from the sale of products and by-products harvested plus the value of crops internally consumed minus all the expenses farmers incurred; this is reported in the first line of Table 6. All data from Giné and Yang (2009) were collected during the survey in 2006; however, the section regarding agricultural production reports retrospective information reflecting the value and cost of production in 2005.

The data also provide interesting insights in line with the theoretical model. For instance, income from farm work is subject to weather variations, $\eta$, as well as idiosyncratic shocks, $\epsilon$. The lack of rainfall constitutes the main thread to groundnut production, as indicated in Table 7. Pest infestation is the second most-cited source of problems, while input price variations are a major concern for fewer than 2% of farmers.

Finally, it is interesting to note that Giné and Yang (2009) test farmers’ willingness to purchase insurance or take out a loan asking questions about hypothetical financial products. More than 90% of farmers are willing to buy both of them, suggesting that existing capital markets cannot meet the demand. To understand whether these positive synergies bear out, I also investigate how the joint supply of weather insurance and credit affects farmers’ consumption, investment and welfare.

An ample margin of welfare improvements from weather insurance alone is nevertheless suggested by the findings reported in Table 8: almost two third of the farmers had to reduce their children’s meals to smooth consumption, and about three fourths of them forecast that in case of drought, they would face a food shortage, indicating a generalized inability to effectively cope against this bad weather shock.

### 4.2 Identification and estimation strategy

The estimation of $\alpha$ and $\sigma_\epsilon$ is performed by indirect inference, matching moments of the ratio $\frac{w_{t+1}}{k_t}$ from the simulated “baseline” model with their empirical counterparts. It can be numerically shown that the targeted moments of $\frac{w_{t+1}}{k_t}$ are independent of both $A_i$ and $a_i$ which act only as scaling factors, and are normalized to $a_i = 1$, and $A_i = 10$, $\forall i$.

To pin down $\alpha$ I match the median of the ratio $\frac{w_{t+1}}{k_t}$ computed from the survey data with that derived from the model simulation. To understand why this provides sufficient identification, consider the following simplified example. In the absence of investment risk (i.e., allowing farmers to insure against investment risk), agents decide how to allocate their resources between consumption and investment, by equating the expected marginal value from an extra unit of investment to the marginal value of an extra unit of consumption. The steady state condition is thus $\frac{\partial w_{t+1}}{\partial k_t} = \frac{1}{\beta}$.

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16 The value of internal consumption is calculated as the product of the difference between the amount produced and the amount sold and the specific price for each crop.
Since investment is risk free, this condition can be explicitly solved leading to $\alpha k_t^{\alpha-1} = \frac{1}{\beta}$, and $k_t^* = \left(\frac{1}{\alpha \beta}\right)^{\frac{1}{\alpha-1}}$. Substituting $k_t^*$ into $\frac{w_{t+1}^i}{k_t}$ leads to $\frac{w_{t+1}^i}{k_t} = \left(\frac{1}{\alpha \beta}\right)^{\frac{\alpha-1}{\alpha-1}} = \frac{1}{\alpha \beta}$, which shows that the wealth to capital ratio can identify $\alpha$ given a calibrated value of $\beta$.

To show that this intuition is also applicable in the presence of risk, I solve the “baseline” model under two different levels of $\alpha$, $\alpha_2 > \alpha_1$, and show that they imply different optimal levels of capital, $k_2^* > k_1^*$. The optimal level of capital, $k^*$, is computed as the value of $k_t$ that is consistent with the target level of wealth. In Figure 3 the red and blue solid lines correspond to the production functions under $\alpha_1$ and $\alpha_2$ respectively, while the dashed lines capture the ratio of $w_t$ to $k_t$ at the optimal point. Ceteris paribus an increase in $\alpha$ leads to a reduction in the optimal ratio of farm income to total capital invested. Note that the structural estimation is performed by matching the median of simulated and actual $\frac{w_{t+1}^i}{k_t}$ instead of the mean, to correct for potential bias due to outliers.

Figure 3: Identification strategy for the share of capital, $\alpha$

Finally, to estimate the variance of the idiosyncratic shock, $\sigma^2$, I match the degree of dispersion of $\frac{w_{t+1}^i}{k_t}$, measured by its standard deviation (SD), $\sigma(\frac{w_{t+1}^i}{k_t})$. Quite intuitively, the higher is the SD of the idiosyncratic shocks, the larger the observed dispersion of the ratio $\frac{w_{t+1}^i}{k_t}$.

I estimate $\alpha$ and $\sigma_\epsilon$ by minimizing the distance between the simulated and actual data. In particular, I guess an initial value for $\alpha$ and $\sigma_\epsilon$, and then solve the “baseline” framework. Using the policy functions, I simulate the consumption and investment responses of 1,000 agents subject to idiosyncratic and aggregate shocks over time. The latter correspond to the year-specific realization of weather shocks measured with the actual data from Malawi. At the end of each simulation, I compute the median and SD of $\frac{w_{t+1}^i}{k_t}$ to be matched with their empirical counterparts. This procedure is repeated to search for the values of $\alpha$ and $\sigma_\epsilon$ that minimize the gap between the empirical and simulated moments.\(^{17}\)

Figure 4 represents the contour plot for the joint estimation of the parameters. The level curves show parameters’ combinations generating equal deviations between simulated and actual moments.

\(^{17}\)The backward-induction solution method is described in greater details in Appendix A.
and darker regions indicate lower distance. The area where the level curves converge identifies the values of $\alpha$ and $\sigma_\epsilon$ that minimize the difference between the simulated and actual median and SD of $w^{t+1}/k_t$. The estimated values and standard deviations are reported in Table 1. Specifically I find

$$0.3 \quad 0.4 \quad 0.5 \quad 0.6 \quad 0.7$$

that $\alpha$ is 0.39, and $\sigma_\epsilon$ is 0.54. The standard errors are computed using a bootstrap procedure, repeating the estimation for 100 times over a sample of 500 observations chosen with replacement from Giné and Yang (2009) data.

### 5 Welfare gains from weather insurance

To understand the impact of weather insurance it is useful to compare the policy functions with (“insurance”) and without (“baseline”) insurance. As discussed in Section 3, a priori it is not possible to determine if weather insurance increases or reduces investment. Figure 5 shows that under the estimated and calibrated parameters values the latter hold true. Indeed, at any level of wealth the availability of insurance leads to higher consumption and lower investment. Because by weakening the precautionary motives to overinvest, weather insurance allows for higher consumption at any given level of wealth. Figure 5 also shows the target level of wealth under the “baseline” and “insurance” frameworks identified by the vertical dashed lines.

The fact that insurance increases consumption and reduces investment is also shown in Figure 6, which plots the dynamics for wealth, consumption and investment if, originally endowed with the “baseline” optimal level of wealth, farmers are unexpectedly and suddenly offered weather insurance. As soon as insurance becomes available, farmers increase consumption and cut investment. This consequently lowers future income, leading over time to a gradual decline in consumption.
However households are able to sustain an ultimately higher level of consumption than without insurance, since the marginal productivity of capital increases and the reduction in investment allows farmers to consume more from each unit of farm income earned.\(^{18}\)

\[\chi_t \text{ such that } \mathbb{E}_t \sum_{j=0}^{\infty} \beta^j u(c_{t+j}(1 + \chi_t)) = \mathbb{E}_t \sum_{j=0}^{\infty} \beta^j u(c_{t+j}^{\text{Insurance}}).\]

Notice that in the qualitative analysis of the model in Figure 1 (top middle plot) the ultimate level of consumption was lower than without insurance following a reduction in investment. This is because different values of \(\alpha\) were used implying a lower response in the marginal productivity of capital.
CRRA utility function, the percentage increase in consumption can also be expressed more clearly as follows:

\[(1 + \chi_t)^{1-\rho} V^{\text{“baseline”}}(w_t) = V^{\text{“insurance”}}(w_t)\]

that is \(\chi_t = \left(\frac{V^{\text{“insurance”}}(w_t)}{V^{\text{“baseline”}}(w_t)}\right)^{\frac{1}{1-\rho}} - 1\)

Evaluated at the “baseline” target level of wealth, the welfare gains from weather insurance corresponds to a permanent increase in consumption of 16.9 percentage points. This is clearly quite a substantial welfare enhancement. Interestingly, gains are an increasing function of wealth, since removing investment uncertainty is particularly beneficial for those richer households with an initial larger investment.

A final interesting insight that can be gained by exploiting the dynamic structure of the model concerns the evolution of welfare gains over time. It is possible to investigate the persistence of the gains and consequently the impact of today’s provision of weather insurance on future generations.
of farmers. Figure 8 shows that the welfare gains from the introduction of weather insurance at time \( t^* \) tend to decline over time. This is caused by the falling level of investment, which lowers future income and harms farmers’ welfare. It is interesting to consider that this result is obtained in an infinite-horizon framework, which incorporates already complete bequest motives, so that parents care about their children as much as themselves. In Section 6 I show that weather insurance may actually lead to increasing welfare gains over time if the insurance allows for the adoption of a more productive technology.

5.1 Synergies between weather insurance and credit

The analysis has shown that the provision of insurance by itself can provide substantial welfare gains. I now seek to investigate if and by how much the welfare-enhancing impact of insurance can be further magnified by the joint provision of credit. I extend the model to allow for borrowing to study possible synergies between credit and insurance as well as the relative potential.

In the absence of insurance when farmers are allowed to borrow to finance investment, the optimization problem (“credit” framework) can be expressed as:

\[
V(w_t) = \max_{k_t, d_t \geq 0} \left[ u(c_t) + \beta E_t V(w_{t+1}) \right]
\]

\[
w_t = c_t + k_t - d_t
\]

\[
w_{t+1} = A_i \epsilon_{i,t} k_t^{\alpha} a_t^{1-\alpha} \eta_{t+1} - Rd_t
\]

\[
k_t - d_t \geq 0
\]

where \( R \) is the risk-free interest rate a farmer pays on the loan of size \( d_t \). Note that this specification rules out the possibility of default, since farmers are always liable for their debt. This is necessary to avoid confusing welfare gains from credit with those from insurance. If farmers could default on debt, they would do so when hit by a bad weather shock and achieve some form of insurance. The inability to default limits the amount of credit that farmers can obtain, since debt must be repaid even if the worst shocks are realized. In particular, the maximum amount of loan obtainable must be such that \( Rd_t = A_i \min (\epsilon_{i,t}) k_t^{\alpha} a_t^{1-\alpha} \min (\eta_{t+1}) \), so that agents are able to pay back their loan even if they are hit simultaneously by the worst idiosyncratic and aggregate weather shocks.\(^{19} \)

Above and beyond this condition, I impose that farmers can borrow at most as much as they invest in productive assets through the constraint \( k_t - d_t \geq 0 \) which is equivalent to state \( w_t - c_t \geq 0 \).

In the presence of credit, the first-order conditions for capital and debt are respectively:

\[
u'(c_t) = \max[\beta E_t[u'(c_{t+1}) \alpha A_i \epsilon_{i,t} k_t^{\alpha} a_t^{1-\alpha} \eta_{t+1}], u'(w_t)]
\]

\[
E_t[u'(c_{t+1}) \alpha A_i \epsilon_{i,t} k_t^{\alpha} a_t^{1-\alpha} \eta_{t+1}] = \max[R E_t[u'(c_{t+1})], E_t[u'(c_{t+1}) \alpha A_i \epsilon_{i,t} (w_t - c_t)^{\alpha} a_t^{1-\alpha} \eta_{t+1}]]
\]

\(^{19} \)When I solve the model, as common in the literature, I discretize the distribution of the idiosyncratic shock, \( \epsilon_{i,t} \), and assume that it is truncated thus maintaining that \( \min (\epsilon_{i,t}) > 0 \). Such approximation has no effect on the estimation of welfare gains from insurance since farmers observe the realization of the idiosyncratic shock before purchasing the insurance.
The former condition states that in the unconstrained region the marginal utility from consumption today must equal the future expected marginal utility from investing one more unit of capital. The latter condition indicates that when the constraint \(k_t - d_t \geq 0\) is not binding, the marginal value of investment must equal the marginal cost of borrowing.

To explore the existence of synergies between the supply of weather insurance with that of credit, I also allow farmers to purchase actuarially fair weather insurance, and borrow to finance the desired additional investment. The optimization problem (“insurance plus credit” framework) can be written as:

\[
V(w_t) = \max_{k_t, d_t \geq 0} [u(c_t) + \beta \mathbb{E}_t V(w_{t+1})]
\]

\[
w_t = c_t + k_t - d_t
\]

\[
w_{t+1} = A_i \epsilon_{i,t} k_t^{\alpha_i} a_i^{1-\alpha_i} \mathbb{E}_t \eta_{t+1} - \mathcal{R} d_t
\]

\[
k_t - d_t \geq 0
\]

where \(\mathbb{E}_t \eta_{t+1}\) is derived from substituting the definition of the actuarially-fair price, \(P_t\) in the expression \(\eta_{t+1} + (1 - \eta_{t+1} - P_t)\). Similar to the “credit” framework, I rule out default. However, it is important to note that households are now able to borrow more once weather insurance is available. Under the “insurance” regime the maximum size of a loan is such that \(\mathcal{R} d_t = A_i \min (\epsilon_{i,t} k_t^{\alpha_i} a_i^{1-\alpha_i} \mathbb{E}(\eta_{t+1})\), while under the “credit” regime farmers do not have protection from weather tail risk and thus cannot borrow more than \(d_t\) such that \(\mathcal{R} d_t = A_i \min (\epsilon_{i,t} k_t^{\alpha_i} a_i^{1-\alpha_i} \min (\eta_{t+1})\). The first-order conditions are analogous to the case with only credit, but removing weather uncertainty.

Figure 9: Policy functions for consumption and investment derived from “baseline”, “insurance”, “credit” and “insurance plus credit” frameworks

Figure 9 compares the policy function for consumption and investment in the absence of insurance and credit (“baseline”), with only insurance (“insurance”), with only credit (“credit”) and with both (“insurance plus credit”). The “baseline” and “credit” policy functions are almost per-
fectly overlapping, thus indicating that the provision of credit per se does not significantly affect agents’ consumption and investment decision. This is because farmers cannot take out large loans since the worst aggregate and idiosyncratic shocks are very disruptive and severely limit the maximum amount they can borrow. The interest rate on debt, $R$, is quite high about 30% per year, but the fact that borrowing is expensive does not play a significant role in determining the gains from credit as shown in the sensitivity analysis in Section 5.2.

The joint provision of insurance and credit reveals strong synergies. Protection against weather shocks substantially increases farmers’ ability to borrow. This is evident from the implied relaxation of the non-default limit of debt. As previously discussed, when investment is risky farmers can at most borrow $d_t$ such that $Rd_t = A_t \min (\epsilon_{t,1}) k_t^\alpha a_t^{1-\alpha} \min (\eta_{t+1})$. However, once weather insurance is supplied, the magnitude of $d_t$ increases substantially to a level such that $Rd_t = A_t \min (\epsilon_{t,1}) k_t^\alpha a_t^{1-\alpha} \mathbb{E} (\eta_{t+1})$. The increase in investment financed through credit is particularly significant for poorer households who face higher investment returns given their small production scale. In particular at a very low level of wealth households consume all their resources, $c_t = w_t$, and invest as much as they can borrow ($k_t = d_t$), so that the policy function for investment is horizontal over a fairly wide range of wealth. Once agents become rich enough that they do not depend solely on credit to finance their activity (indicated by the wedge between the amount of capital invested $k_t$ and borrowed $d_t$), the consumption function become strictly concave.

![Figure 10: Dynamic responses of wealth, consumption and investment to the introduction of “credit” and “insurance plus credit”](image)

The importance of credit and its synergies with weather insurance are also captured by the impulse response functions in figure 10 which show how wealth, consumption and investment evolve once insurance and credit are offered at time $t^*$ to farmers originally endowed with the “baseline” target level of wealth. As when only weather insurance is supplied, farmers react by expanding consumption and contracting investment because of the decline in precautionary motives. The
responses, however, are very small when only credit is provided.

Moving to the welfare comparison, Figure 11 plots the value functions and the welfare gains farmers can achieve. The provision of credit alone is welfare enhancing mainly at a low level of wealth, given that richer households do not find it convenient to raise costly external financing when facing lower investment returns. Poorer farmers also benefit the most when both insurance and credit are available. It is interesting to note that the joint provision of insurance and credit enables farmers to benefit more than if credit and insurance were separately offered, revealing strong synergies between weather insurance and credit. Indeed the gains from only credit and only insurance measured at the “baseline” target level of wealth respectively amount to a 0.4% and 16.9% permanent increase in consumption, while those from “insurance plus credit” correspond to a 18.9% permanent increase in consumption.

Finally regarding the evolution of welfare gains over time figure 12 shows that benefits are fairly stable with only credit and decline over time when insurance is also provided.
5.2 Sensitivity Analysis

In this section, I explore the sensitivity of the welfare gains to the key parameters values. In particular, I consider how welfare gains change at the “baseline” target level of wealth with respect to one-at-a-time variations in \( \alpha, \sigma, \epsilon, \beta, R, \) and \( \rho \) holding constant the other parameters. Results are reported in figure 13.

![Figure 13: Sensitivity analysis of welfare gains with respect to the model parameters](image)

Figures 13(a), 13(b) and 13(c) show that welfare gains from weather insurance increase in \( \alpha, \sigma, \) and \( \epsilon \). In reference to the possible concern expressed in Appendix B that the discount factor \( \beta \) is somewhat lower than other values used in the literature, the sensitivity plot shows that a higher \( \beta \) would imply even higher welfare gains.

The sensitivity to the interest rate \( R \) is shown in Figure 13(d) which reveals that synergies between insurance and credit slightly decrease with \( R \). Interestingly the gains from the provision of only credit are largely unaffected by the magnitude of \( R \) since the large risks to which production is exposed already allows for very little non-defaultable credit.

Finally Figure 13(e) shows that, intuitively, gains are strongly increasing in the relative risk aversion coefficient, \( \rho \). It is interesting to note that when \( \rho = 0.9 \) even if the provision of weather insurance causes an initial fall in consumption (see Section 3), yet it is highly welfare enhancing, \( \chi^{\text{insurance}} = 4.8\%, \chi^{\text{insurance plus credit}} = 5.6\%, \chi^{\text{credit}} = 0.3\% \).
6 Adoption of riskier but more productive technology

Section 5 showed that weather insurance may lead to decreasing investment and thus declining welfare gains over time. This result, however, may be overturned when farmers can choose between technologies with different risk-productivity combinations. In particular, I explore the possibility that by being better equipped to cope against destructive weather shocks, farmers may change the allocation of their resources and invest more in higher-return, higher-volatility assets thus achieving higher income and consumption.

As documented by the agricultural and development literature, the inability to protect themselves against weather risks forces farmers in developing countries to make conservative investment choices which can perpetuate poverty. Fafchamps and Kurosaki (2002) and Dercon and Christiaensen (2007) claim that low probability, but highly destructive weather shocks may induce farmers to underinvest in high return, but also high volatility projects, limiting household ability to emerge from poverty. Similarly, Chetty and Looney (2006) demonstrate that observing a priori small consumption fluctuations should not lead to underestimate the need for insurance; rather, it may indicate that because of their limited ability to cope with risk, agents select into low-volatility, but also low-return activities.

The bias toward safer investment is particularly strong among poorer households. Analyzing the investment portfolios of farmers per wealth quintile, Rosenzweig and Binswanger (1993) show that poorer households adopt less efficient and less productive techniques in order to minimize weather risks. Similar conclusions are reached by Zimmerman and Carter (2003) who, allowing for divisible assets and fully rational agents, show that optimal portfolio strategies are a bifurcate function of wealth. While richer agents acquire high return assets for consumption smoothing, poorer households invest in a lower return portfolio to reduce volatility. Collier and Gunning (1999) and Eswaran and Kotwal (1990) suggest that this can be due to the presence of initial start-up costs that poorer households cannot afford. I show that the existence of initial fixed costs is not a necessary condition to account for the empirical evidence.

A particularly relevant issue for farmers in Malawi is the decision to use hybrid versus traditional seeds which involves a trade off between returns and volatility. Simtowe (2006) reports that Malawian local crops perform better than their hybrid counterparts (potentially more productive) during times of weather stress. Furthermore, as argued by Duflo, Kremer and Robinson (2008), to maximize hybrid yields farmers need to apply fertilizer, an expensive farm input with volatile returns, and must apply it twice: at sowing time and as top-dressing during the growing season. However if it rains too little and the seed does not germinate the investment in both seed and fertilizer is completely lost, corresponding to a substantial loss. Survey data from Giné and Yang (2009) confirm that farmers are aware of this trade-off and modify their decisions accordingly. Indeed, when asked about their response to an expected bad weather shock, they emphasize the importance of selecting the right crop variety (Table 9).
6.1 Theoretical framework

Following these insights, I extend the framework of analysis and allow farmers to invest in two crops—traditional and hybrid seeds—which differ in terms of their rate of return and riskiness. As in Section 3, I first lay out the “baseline” framework and then allow for the provision of weather insurance.

When farmers can invest in two crops, the dynamic stochastic optimization problem they face can be expressed as follows:

\[
V(w_t) = \max_{k_t, l_t} \left[u(c_t) + \beta \mathbb{E}_t V(w_{t+1})\right]
\]

where \(A_h\) and \(A_i\) are the total factor productivities, and \(\eta_{t+1,h}\) and \(\eta_{t+1,i}\) are the aggregate weather shocks respectively for hybrid and traditional crops. Hybrid crops are on average more productive than traditional crops, that is \(A_h > A_i\), but their yields are also more volatile, \(Var(\eta_{t+1,h}) > Var(\eta_{t+1,i})\). Each crop is produced using as input its technology-specific capital \(k_{t,h}\) or \(k_{t,i}\), and labor \(l_{t,h}\) or \(l_{t,i}\). The constraint \(l_{t,h} + l_{t,i} = 1\) indicates that the total amount of labor is normalized to 1. Notice that when farmers invest only in one crop, all their labor is allocated to the production of that crop, and thus labor was not explicitly included as a choice variable when only crop was considered (framework 1).

The first-order conditions for investment and labor are:

\[
\begin{align*}
V(w_t) &= \max_{k_t, l_t} \left[u(c_t) + \beta \mathbb{E}_t V(w_{t+1})\right] \\
V(w_t) &= c_t + k_{t,h} + k_{t,i} \\
w_{t+1} &= A_h \epsilon_i, t k_{t,h}^{\alpha} \eta_{t+1,h} + A_i \epsilon_i, t k_{t,i}^{\alpha} \eta_{t+1,i} \\
l_{t,h} + l_{t,i} &= 1
\end{align*}
\]

The first two equations are the first-order condition with respect to \(k_{t,h}\) and \(k_{t,i}\) requiring today’s marginal utility of consumption to tomorrow’s expected marginal utility from investment. The last equation is the optimality condition with respect to labor indicating that the marginal productivity of labor is equalized across crops.

As when only one crop is produced, I expand the framework of analysis and introduce the possibility to purchase actuarially fair weather insurance. I also retain the assumption that farmers can observe their productivity shock before deciding how much insurance to purchase, implying full insurance. The dynamic stochastic optimization problem can be expressed as

\[
V(w_t) = \max_{k_t, l_t} \left[u(c_t) + \beta \mathbb{E}_t V(w_{t+1})\right]
\]

where \(\eta_{t+1,h}\) and \(\eta_{t+1,i}\) are the aggregate weather shocks respectively for hybrid and traditional crops. Hybrid crops are on average more productive than traditional crops, that is \(A_h > A_i\), but their yields are also more volatile, \(Var(\eta_{t+1,h}) > Var(\eta_{t+1,i})\). Each crop is produced using as input its technology-specific capital \(k_{t,h}\) or \(k_{t,i}\), and labor \(l_{t,h}\) or \(l_{t,i}\). The constraint \(l_{t,h} + l_{t,i} = 1\) indicates that the total amount of labor is normalized to 1. Notice that when farmers invest only in one crop, all their labor is allocated to the production of that crop, and thus labor was not explicitly included as a choice variable when only crop was considered (framework 1).

The first-order conditions for investment and labor are:

\[
\begin{align*}
V(w_t) &= \max_{k_t, l_t} \left[u(c_t) + \beta \mathbb{E}_t V(w_{t+1})\right] \\
V(w_t) &= c_t + k_{t,h} + k_{t,i} \\
w_{t+1} &= A_h \epsilon_i, t k_{t,h}^{\alpha} \eta_{t+1,h} + A_i \epsilon_i, t k_{t,i}^{\alpha} \eta_{t+1,i} \\
l_{t,h} + l_{t,i} &= 1
\end{align*}
\]

The first two equations are the first-order condition with respect to \(k_{t,h}\) and \(k_{t,i}\) requiring today’s marginal utility of consumption to tomorrow’s expected marginal utility from investment. The last equation is the optimality condition with respect to labor indicating that the marginal productivity of labor is equalized across crops.

As when only one crop is produced, I expand the framework of analysis and introduce the possibility to purchase actuarially fair weather insurance. I also retain the assumption that farmers can observe their productivity shock before deciding how much insurance to purchase, implying full insurance. The dynamic stochastic optimization problem can be expressed as
\[ w_{t+1} = A_h \epsilon_{t,h} k_{t,h}^{\alpha} l_{t,h}^{1-\alpha} \left( \eta_{t+1,h} + (1 - \eta_{t+1,h}) - P_{t,h} \right) \]
\[ + A_t \epsilon_{t,t} k_{t,t}^{\alpha} l_{t,t}^{1-\alpha} \left( \eta_{t+1,t} + (1 - \eta_{t+1,t}) - P_{t,t} \right) \]
\[ l_{t,h} + l_{t,t} = 1 \]

where \( P_{t,h} \) and \( P_{t,t} \) correspond to the insurance premium for the traditional and hybrid crop which are defined as \( P_{t,h} = \int_0^1 (1 - \eta_h) f(\eta_h) d\eta_h \) and \( P_{t,t} = \int_0^1 (1 - \eta_t) f(\eta_t) d\eta_t \).

When farmers are able to purchase weather insurance, the production of hybrid crops becomes as risky as that of traditional ones since they are both subject to only the common idiosyncratic productivity shocks. Yet hybrid crop remains more productive, since
\[ A_h(1 - P_{t,h}) = A_h E_{\eta_{h,t+1}} > A_t E_{\eta_{t+1,t}} = A_t(1 - P_{t,t}), \]
in inducing farmers to completely shift their investment from traditional to hybrid seeds. Hence, by purchasing actuarially-fair insurance, every farmer is able to fully invest in the most productive technology, irrespectively of his initial level of wealth.

Moreover, it is important to note that the solution of the optimization problem when insurance is available is largely simplified, since it can be solved following the same strategy as if farmers were allowed to invest in only one crop. Indeed, the first-order condition for capital is simplified to:
\[ u'(c_t) = \beta E_t [u'(c_{t+1}) A_h \epsilon_{t,h} k_{t,h}^{\alpha} (1 - P_{t,h})] \]

where the marginal utility of consumption today equals the expected marginal utility of consumption tomorrow given that farmers invest only in the most productive technology available.

### 6.2 Empirical results

To investigate the impact of weather insurance on consumption, investment, and welfare when farmers can invest in two crops whose yields differ in terms of return/volatility, I solve the “baseline” (7) and “insurance” (9) frameworks using the parameters calibrated and structurally estimated in Section 5, except I now allow the aggregate weather shock and the total factor productivity terms to vary between crops.

Using the CWSA designed by Osgood et al. (2007), I derive the empirical distribution of the aggregate weather shocks for traditional and hybrid crops, \( \eta_t \) and \( \eta_h \). Their probability density function is plotted in figure 14 where the dashed bars referring to \( \eta_t \) and the solid bars refer to \( \eta_h \). The yields from hybrid crops are much more volatile in response to weather fluctuations, since the SD of the empirical distribution of \( \eta_h \) is more than twice as large as that of \( \eta_t \) (\( \sigma_{\eta_h} = 0.23, \sigma_{\eta_t} = 0.1 \)). The total factor productivities are such that \( A_h = 1.5 A_t E_{\eta_t} \) since hybrid crops are 50% more productive than traditional ones according to Malawi Department Meteorological Services (2007).

Figure 15 plots the policy functions for consumption and capital under the “baseline” (black lines) and “insurance” (blue lines) framework. In the “baseline” regime, farmers invest in both crops and, consistent with the empirical evidence, the proportion of capital invested in hybrid is an increasing function of wealth. Indeed, the share is about 40% for poorer farmers and rises to about 60% at the target level of wealth. As seen in the right plot, the policy functions for hybrid and
traditional investment almost overlap at low levels of wealth, but a wedge opens between them as wealth increases. As anticipated in Section 6.1 when weather insurance becomes available, farmers fully invest in hybrid crops. This leads to higher income and therefore higher consumption as illustrated by the fact that the consumption function move upwards at any level of wealth.

This is further reflected in the dynamic responses of consumption and capital following the introduction of insurance (Figure 16). As soon as farmers are able to purchase weather insurance they increase the amount of capital invested in hybrid crops and simultaneously boost their consumption. Similar to the case when farmers plant only one type of crop, the overall level of investment \((k_{t,t} + k_{t,h})\) falls as soon as weather insurance becomes available. However now the increase in the amount of capital invested in more productive hybrid crops, \(k_{t,h}\), is enough to guarantee both higher income and higher consumption in the following periods.

The increase in consumption is reflected in Figure 17 which shows the value functions for the “baseline” and “insurance” regimes as well as the welfare gains if weather insurance is offered to farmers. At the target level of wealth when two crops are available the provision of insurance leads to a perennial increase in consumption of nearly 23.4\%, 6 percentage points higher than if farmers could invest in only one crop. Moreover, these welfare gains are persistent across generations (Figure 18). In the case of one crop welfare gains from weather insurance are lower for future generations relative to current ones. This is no longer true in the case of two crops since weather insurance allows farmers to invest in higher productivity seeds, leading to higher income and thus higher future consumption.
Figure 15: Policy functions for consumption and investment when farmers plant hybrid and traditional crops

Figure 16: Dynamic responses of wealth, consumption and investment to the introduction of weather insurance when farmers plant hybrid and traditional crops

7 Factors hindering take-up

Despite the potentially large welfare gains from weather insurance identified thus far, experimental evidence has often somewhat surprisingly documented low take-up (see for instance by Cole et al. (2009), and Giné and Yang (2009)). In this section, I explore three different factors that may explain this finding. First, the insurer may charge a loading factor to cover the administrative costs. Second, the insurance payments may not perfectly compensate for the actual losses experienced by farmers due to the presence of basis risk. Differences in soil composition or exposure, or in the slope of the plots can indeed change the impact of rainfalls on yields, thus preventing the insurer from accurately predicting the losses suffered by households. Similar issues arise for farmers who live farther away and experience different rainfall patterns than those measured by the weather stations. Third, so far I have assumed that the purchase of weather insurance takes place after the realization of other insurable idiosyncratic shocks. If this is not the case, I show that farmers will optimally choose a lower take-up. Each of these elements potentially contributes to reducing the purchase of weather insurance and associated benefits.

I proceed to incorporate these factors into the model to quantitatively evaluate their impact on
the insurance take-up and the relative welfare gains. The optimization problem can be expressed as follows:

\[ V(w_t) = \max_{k_{t+1} \geq 0} [u(c_t) + \beta E_t V(w_{t+1})] \]
\[ w_t = c_t + k_t \]
\[ w_{t+1} = A_t \epsilon_{t+1} k_t^{\alpha} u_{t+1}^{1-\alpha} + t_t (1 - \eta_{t+1}) \xi_{t+1} - t_t P_t (1 + \theta) \]

where \( \xi_{t+1} \) is an error term log-normally distributed with mean 1 and variance \( \sigma_\xi^2 \), providing a measure of basis risk, and the constant \( \theta \) corresponds to the loading factor charged by the insurer. Basis risk becomes more acute as the variance of \( \xi \) increases since the higher \( \sigma_\xi^2 \) the lower the correlation between the insurance payments and the actual losses. Furthermore I assume that farmers decide how much insurance to buy before they observe their idiosyncratic productivity.
The first-order conditions for $k_t$ and $\iota_t$ respectively are given by

\begin{align*}
    u'(c_t) &= \beta E_t u'(c_{t+1})(\alpha A_i \epsilon_{i,t} k_t^{\alpha-1} a_1^{1-\alpha} \eta_{t+1}) \\
    \beta E_t u'(c_{t+1})(1 - \eta_{t+1}) \xi_{t+1} &= \max\{\beta E_t u'(c_{t+1}) P_t (1 + \theta), 0\}
\end{align*}

where the former states that the marginal utility from consumption today must equal the expected discounted marginal utility from consumption tomorrow, and the latter indicates that farmers would purchase as much insurance as necessary to equate the marginal cost to the marginal benefit.\textsuperscript{20}

To solve the model, the values of $\theta$ and $\sigma_{\xi}$ need to be determined. I assume that $\theta = 0.175$, given that a government tax of 17.5% was mandated in the implementation of Giné and Yang (2009) randomized experiment. The benchmark value of basis risk to which farmers are exposed to is not clear, so I simply set $\sigma_{\xi} = 0.54$ (roughly corresponding to $\sigma_{\epsilon}$) which leads to a correlation between insurance payments and actual losses of 0.73. I perform sensitivity analysis with respect to these parameters at the end of this section.

\begin{figure}[h]
\centering
\includegraphics[width=\textwidth]{figure19.png}
\caption{Weather insurance take-up rate if idiosyncratic shocks are (un)observable, and there is basis risk ($\xi$) and a loading factor ($\theta$)}
\end{figure}

In the setting previously studied without basis risk, loading factor and with the possibility to observe idiosyncratic shocks before purchasing weather insurance, farmers fully protect against investment risk, $\iota_t = A_k^\epsilon a_1^{\alpha-\alpha} \epsilon_{i,t}$, thus achieving an insurance take-up rate of 100%. However, once these factors are accounted for this no longer holds true. Figure 19 shows the take-up rate measured by the ratio $\frac{\iota_t}{A_k^\epsilon a_1^{\alpha-\alpha} \epsilon_{i,t}}$, under each of these factors separately considered and when jointly present. Each factor can reduce take-up rate quite substantially up to 50%. When all elements are contemporaneously introduced the take-up dramatically shrinks to less than 20%.

It is interesting to note how basis risk, loading factor, and unobservability of idiosyncratic shocks affect the magnitude of the welfare gains (Figure 20). The percentage reduction in take-up due to the first two factors is mirrored by an equivalent fall in welfare gains, which drop by about 50% from an equivalent permanent increase in consumption of 16.9% to 9.4% when only basis risk is

\textsuperscript{20}The first order condition with respect to $\iota$ when $\epsilon$ is observable becomes $\beta E_t u'(c_{t+1}) \epsilon_{i,t} (1 - \eta_{t+1}) \iota_{t+1} = \max\{\beta E_t u'(c_{t+1}) \epsilon_{i,t} P_t (1 + \theta), 0\}$. 

28
included or to 7.8% when a loading factor is charged. Conversely, welfare gains drop only by nearly 2 percentage points down to 14.9% when $\theta = 0$ and $\sigma_\zeta = 0$, but farmers are unable to buy weather insurance before observing idiosyncratic shocks. Clearly, the largest fall happens when all three elements are at play bringing the welfare gains evaluated at the “baseline” target level of wealth to a 3.6% permanent increase in consumption. Therefore even with a fairly low insurance take-up, the benefits from weather insurance remain quite substantial.

![Figure 20: Welfare gains from weather insurance if idiosyncratic shocks are (un)observable, and there is basis risk ($\xi$) and a loading factor ($\theta$)](image)

Finally I study the sensitivity of the take-up rate and welfare gains to the magnitude of basis risk and loading factor to better understand how the results previously discussed depend on the chosen calibration. Figure 21 plots the take-up rate and relative welfare gains evaluated at the “baseline” target level of wealth. As expected the welfare gains and the take-up rate are negatively correlated with the presence of either basis risk or loading factor. Furthermore we confirm that the impossibility of observing a priori the idiosyncratic risks substantially curbs the take-up rate but only moderately reduces the welfare gains.

Summing up this section has shown that each of the three factors may strongly reduce take-up. However the analysis also reveals that welfare gains may still be quite substantial; thus a low observed take-up should not lead to dismissing the importance of weather insurance. In future research, it would be important to investigate which of these factors is predominant since policy implications to improve weather insurance programs would be quite different. If basis risk is the key element, installing additional weather stations to better monitor local weather would be quite important. If instead the presence of other uninsured idiosyncratic shocks is particularly pervasive, it becomes crucial to bundle weather insurance with protection against other risks.
8 Conclusion

In this paper, I have developed and structurally estimated a dynamic stochastic model of investment and consumption for farmers in developing countries to study the impact of weather insurance. I first quantified the potential welfare gains in the absence of loading factor and basis risk, and when farmers know their idiosyncratic productivity before purchasing insurance. Weather insurance could greatly improve welfare leading to gains equivalent to almost a 17% permanent increase in consumption. By exploiting the dynamic nature of the model I have shown that these benefits however decline over time, because the introduction of weather insurance causes a decline in investment. This occurs because weather insurance reduces the precautionary motives that stimulate overinvestment. I also studied the synergies between credit and insurance and found that the joint provision of both can be particularly beneficial for poorer households.

In an extension of the model allowing for two different investment opportunities, I have shown that welfare gains are not necessarily shrinking over time. Weather insurance may indeed induce farmers to invest more in a riskier but more productive technology, such as hybrid seeds. This

Figure 21: Sensitivity analysis of welfare gains and weather insurance take-up with respect to the model parameters
further boosts the welfare gains and especially leads them to increase over time because of the increase in farmers’ income.

Given the large potential welfare gains predicted by the model, it becomes important to understand why the take-up of weather insurance has not been empirically as high as expected. I thus study the extent to which the benefits may be lowered by the interplay with other uninsurable risks, or the presence of loading factor and basis risk. The latter two elements can moderately reduce both the take-up and welfare gains from weather insurance by similar amounts. Conversely, the inability to protect investment from risks other than weather fluctuations (such as pests, or farmers’ illness) significantly reduces the weather insurance take-up, even though it leaves almost unchanged the magnitude of welfare gains obtainable. This is an interesting result since it suggests that a low take-up should not automatically lead to dismissing the benefits from weather insurance which may still be sizeable.

In future research I plan to investigate more closely the specific factors hindering weather insurance take-up since they could lead to different policy implications. Installing additional weather stations could be the proper solution if basis risk is found to reduce welfare gains the most. Alternatively, providing coverage against uninsured idiosyncratic risks along with weather insurance would be essential if the inability to protect investment from other shocks is the most welfare-detrimental element.
Appendix

A Policy functions solution method

In order to describe the numerical solution procedure pursued to solve for the policy function, I focus for simplicity on the “baseline” regime, where agents invest in only one crop, cannot finance investment through credit nor protect their consumption by purchasing weather insurance. I follow a similar strategy for the “insurance”, “credit”, and “insurance plus credit” frameworks and note whenever significant differences in the solution procedure arise.

Due to the presence of risk in the production function, it is not possible to derive a closed-form solution for the frameworks presented in Section 3, and I thus need to solve for the policy functions numerically. To do that I first derive the first-order conditions:

\[(c_t(w_t))^{-\rho} = \beta \mathbb{E}(\alpha \epsilon_{i,t+1} (\alpha_{t+1} k_{t+1}^{\alpha-1} q_{t+1}) \frac{\partial V(w_{t+1})}{\partial k_{t+1}})\]

Then, following the method of endogenous gridpoints developed by Carroll (2006), by backward iteration I solve the consumption function initialized at the (hypothetical) last period of life when the agents consume all their resources. For all previous periods, I define a grid for \(k_t\) and given the first-order condition I can compute the value of \(c_t\) consistent with each value of capital invested, \(k_t\). Using the budget constraint I easily recover the value of wealth, \(w_t = k_t + c_t\), consistent with each combination of consumption and capital previously determined.\(^{21}\) From the linear interpolation of the pairs \((c_t, w_t)\), I construct the consumption function.\(^{22}\)

Finally, to quantify the welfare gains, I need to back up the value function. Using its definition, \(V(w_t) = u(c_t(w_t)) + \beta \mathbb{E}_t V(w_{t+1})\), and the fact that in the (hypothetical) last period all resources are consumed, I initialize the value function to the utility function. For each previous period I use a linear interpolation of the pairs \((V, w_t)\). Possible problems may arise at low levels of wealth where the value function is highly concave. Specifically, the value function evaluated at wealth equal to zero corresponds to negative infinity which is clearly barely tractable. To overcome this issues, Carroll (2006) suggests adopting a transformation of the value function, multiplying it by \((1 - \rho)\) and elevating everything to the power of \(\frac{1}{1-\rho}\), \((V(w_t)(1-\rho))^{\frac{1}{1-\rho}}\), preventing the transformed function from taking a value minus infinity. This process of backward iteration continues until the policy functions converge, that is until the difference between two consecutive consumption and value functions is smaller than 0.01%.

---

\(^{21}\)If agents can borrow, the grid is defined as \(k_t - d_t \geq 0\), which holds with equality when all investment is financed through debt. Since neither default nor credit for consumption is allowed, the expression above can never be negative. When credit is available, to ensure that it is used exclusively for investment I have agents decide the overall optimal amount of capital to invest before any decisions regarding consumption are made, ruling out the possibility that part of \(d_t\) serves to finance consumption.

\(^{22}\)If agents can rely on credit to finance investment, they may decide to consume all their wealth: that is, \(c_t = w_t\) and \(k_t = d_t\) consistent with the budget constraint, \(w_t = c_t + k_t - d_t\). The consumption function for this constrained region is derived by prepending the point \((0,0)\) to a list of pairs \((c_t, w_t)\) used in the linear interpolation.
B Parameter calibration: further details

Coefficient of relative risk aversion, $\rho$. I calibrate the coefficient of constant relative risk aversion $\rho$ and the value for the discount factor $\beta$ using the data about the attitude toward risk based on a series of hypothetical questions whose answers are reported in Table 8. The calculation of the coefficient of relative risk aversion, $\rho$, is based on the following question:

You are going to play a game, I am going to flip a coin. Imagine that you would get the money shown under the GREEN area if it lands on heads or the money shown under WHITE area if it lands on tails. The amount you would win depends on the bet you choose. Which bet would you choose? a. 50/50, b. 40/120, c. 30/160, d. 20/190, e. 10/210, f. 0/220

The payoffs can be ranked on the basis of their riskiness, and by equating the expected utility from the different gambles, I compute the upper and lower bounds for the true value of $\rho$, and then take the average of the median value for each interval, as done by De Mel, McKenzie and Woodruff (2008).

Discount factor, $\beta$. The discount factor, $\beta$, is constructed with the answers to these two questions:

1. Imagine that you bought a lottery ticket and you have just won. The prize is MWK1000. You can get the MWK1000 now for sure. However, if you are willing to wait for 30 days, you can get more. What do you prefer:

   (a) \[
   \begin{align*}
   1. & \text{ MWK1000 prize today;} \\
   2. & \text{ MWK1250 prize 30 days from now.}
   \end{align*}
   \]

   (b) \[
   \begin{align*}
   1. & \text{ MWK1000 prize today;} \\
   2. & \text{ MWK1500 prize 30 days from now.}
   \end{align*}
   \]

   (c) \[
   \begin{align*}
   1. & \text{ MWK1000 prize today;} \\
   2. & \text{ MWK1750 prize 30 days from now.}
   \end{align*}
   \]

2. If the answer in a, b, c is “MWK1000 prize today”, then: how much would the prize have to be for you to choose to wait 30 days?

The discount rate is then computed as \[\frac{\text{Prize accepted} - 1000}{1000},\] and the discount factor, $\beta$, is then given by \[\frac{1}{1 + \text{Discount rate}}.\] The point estimate obtained with this method ($\beta = 0.76$) appears low, but is consistent with the findings of Laibson, Repetto and Tobacman (2007), and Duflo, Kremer and Robinson (2009) who use similar values in a recent study of fertilizer adoption in Malawi and Kenya. A caveat should nevertheless be raised regarding the precision of the discount factor’s estimate. In answering the survey question, farmers may provide a combination of both the discount factor and the interest rate they face. For instance if the
return from their activity is higher than the gains they may otherwise obtain by waiting, they may decide to have the money today not because they are impatient, but because it is more profitable to do so. Such misspecification would lead to a downward-biased estimate of $\beta$.

To assess the relevance of this issue in Section 5.2 I show how welfare gains are affected by a change in the point estimate of $\beta$.

**Weather shock, $\eta$.** As anticipated in section 4.1, the distribution of the weather shock is derived from the crop water satisfaction analysis (CWSA) module. Designed by the International Research Institute for Climate and Society at Columbia University, the CWSA module combines soil, crop phenotype, weather databases and management options to simulate crop reaction to water deficit. It is fed with daily time series for the rainfall level from 1961 to 2006, and evaporation data regarding the amount of soil moisture needed to optimize production specific to the four Malawian regions analyzed in Giné and Yang (2009). Using the FAO estimates, are also specified the parameters for each crop’s growth cycle (the crop coefficients $KC$), its reactivity to water shortage during the different phases of this cycle (the varying yield response factors $KY$), and its sensitivity to the crop’s evapotranspiration ($Seasonal KY$). Finally, using Osgood et al. (2007) calculations, for each crop the potential sowing window is fixed to be constant across time and the soil water-holding capacity. This latter assumption plays a crucial role in ensuring that the crop model is influenced only by the rainfall distribution and not by other factors, such as farmer’s ability to forecast the beginning of the rainy season, which would be instead captured in the idiosyncratic productivity term.
### Table 2: Savings: summary statistics

#### Saving deposits with any bank

<table>
<thead>
<tr>
<th>$N^{Tot}$</th>
<th>Mean</th>
<th>SD</th>
<th>$N^{Yes}$</th>
<th>Mean</th>
<th>SD</th>
<th>p10</th>
<th>p50</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes=1</td>
<td>764</td>
<td>20%</td>
<td>151</td>
<td>24378</td>
<td>1500</td>
<td>6000</td>
<td>35000</td>
<td></td>
</tr>
<tr>
<td>In 2005</td>
<td>154</td>
<td>22152</td>
<td>39150</td>
<td>1000</td>
<td>12000</td>
<td>50000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Cash at home

<table>
<thead>
<tr>
<th>$N^{Tot}$</th>
<th>Mean</th>
<th>SD</th>
<th>$N^{Yes}$</th>
<th>Mean</th>
<th>SD</th>
<th>p10</th>
<th>p50</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes=1</td>
<td>764</td>
<td>64%</td>
<td>486</td>
<td>5379</td>
<td>9782</td>
<td>2000</td>
<td>12000</td>
<td></td>
</tr>
<tr>
<td>In 2005</td>
<td>476</td>
<td>7906</td>
<td>11204</td>
<td>500</td>
<td>5000</td>
<td>20000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Non-livestock assets (seeds, bike, etc..)

<table>
<thead>
<tr>
<th>$N^{Tot}$</th>
<th>Mean</th>
<th>SD</th>
<th>$N^{Yes}$</th>
<th>Mean</th>
<th>SD</th>
<th>p10</th>
<th>p50</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes=1</td>
<td>764</td>
<td>53%</td>
<td>402</td>
<td>22252</td>
<td>60103</td>
<td>2000</td>
<td>9000</td>
<td>50000</td>
</tr>
<tr>
<td>In 2005</td>
<td>396</td>
<td>20341</td>
<td>59822</td>
<td>2000</td>
<td>7000</td>
<td>39000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Club or other group revolving fund

<table>
<thead>
<tr>
<th>$N^{Tot}$</th>
<th>Mean</th>
<th>SD</th>
<th>$N^{Yes}$</th>
<th>Mean</th>
<th>SD</th>
<th>p10</th>
<th>p50</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Yes=1</td>
<td>764</td>
<td>7%</td>
<td>49</td>
<td>3902</td>
<td>6069</td>
<td>1000</td>
<td>12000</td>
<td></td>
</tr>
<tr>
<td>In 2005</td>
<td>45</td>
<td>3674</td>
<td>6052</td>
<td>0</td>
<td>900</td>
<td>15000</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

#### Livestock (Donkeys, cows, oxen, goats, sheep, pigs, chickens)

<table>
<thead>
<tr>
<th>$N^{Yes}$</th>
<th>Mean</th>
<th>SD</th>
<th>p10</th>
<th>p50</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>In 2006</td>
<td>764</td>
<td>24670</td>
<td>62612</td>
<td>6350</td>
<td>55000</td>
</tr>
</tbody>
</table>

Note: All calculations are based on retrospective data regarding 2005 and collected during household survey in 2006. $N^{Tot}$ corresponds to the total number of household surveyed, $N^{Yes}$ to the total number of household declaring receiving non-farm income. p10, p50 and p90 correspond respectively to the 10th, 50th, and 90th percentile of the distribution.
Table 3: Non-farm income: summary statistics

<table>
<thead>
<tr>
<th>Source of Income</th>
<th>N(^{Tot})</th>
<th>N(^{Yes})</th>
<th>Mean</th>
<th>SD</th>
<th>Mean</th>
<th>SD</th>
<th>p10</th>
<th>p50</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Wages from agricultural labor</strong></td>
<td>764</td>
<td>764</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes=1</td>
<td>31%</td>
<td>0.46</td>
<td>240</td>
<td>6259</td>
<td>51936</td>
<td>250</td>
<td>1000</td>
<td>5500</td>
<td></td>
</tr>
<tr>
<td><strong>Wages from non-agricultural sector</strong></td>
<td>764</td>
<td>764</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes=1</td>
<td>14%</td>
<td>0.34</td>
<td>104</td>
<td>23591</td>
<td>51404</td>
<td>500</td>
<td>5000</td>
<td>78000</td>
<td></td>
</tr>
<tr>
<td><strong>Wages from public works program</strong></td>
<td>764</td>
<td>764</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes=1</td>
<td>13%</td>
<td>0.34</td>
<td>102</td>
<td>2484</td>
<td>3264</td>
<td>225</td>
<td>2000</td>
<td>4820</td>
<td></td>
</tr>
<tr>
<td><strong>Migration income/Remittance</strong></td>
<td>764</td>
<td>764</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes=1</td>
<td>9%</td>
<td>0.28</td>
<td>66</td>
<td>3626</td>
<td>3540</td>
<td>600</td>
<td>2050</td>
<td>7800</td>
<td></td>
</tr>
<tr>
<td><strong>Benefits from government scheme</strong></td>
<td>764</td>
<td>764</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes=1</td>
<td>9%</td>
<td>0.13</td>
<td>67</td>
<td>3673</td>
<td>3375</td>
<td>500</td>
<td>3000</td>
<td>8500</td>
<td></td>
</tr>
<tr>
<td><strong>Pensions</strong></td>
<td>764</td>
<td>764</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes=1</td>
<td>2%</td>
<td>0.13</td>
<td>13</td>
<td>30335</td>
<td>99163</td>
<td>257</td>
<td>2000</td>
<td>15600</td>
<td></td>
</tr>
<tr>
<td><strong>Other income sources (such as gambling)</strong></td>
<td>764</td>
<td>764</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Yes=1</td>
<td>5%</td>
<td>0.21</td>
<td>36</td>
<td>6539</td>
<td>11574</td>
<td>300</td>
<td>3000</td>
<td>12000</td>
<td></td>
</tr>
</tbody>
</table>

Note: All calculations are based on retrospective data regarding 2005 economic activity, and collected during household survey in 2006. N\(^{Tot}\) corresponds to the total number of household surveyed, N\(^{Yes}\) to the total number of household declaring receiving non-farm income, Mean, SD, p10, p50 and p90 correspond respectively to the mean, standard deviation, 10\(^{th}\), 50\(^{th}\), and 90\(^{th}\) percentile of the distribution.
### Table 4: Total expenditure on farm inputs: summary statistics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>p10</th>
<th>p50</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farm inputs</td>
<td>764</td>
<td>17580</td>
<td>36256</td>
<td>1850</td>
<td>7200</td>
<td>39700</td>
</tr>
<tr>
<td>Irrigation</td>
<td>764</td>
<td>122</td>
<td>1223</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Fertilizer</td>
<td>764</td>
<td>7297</td>
<td>16414</td>
<td>0</td>
<td>2350</td>
<td>16150</td>
</tr>
<tr>
<td>Chemical insecticides</td>
<td>764</td>
<td>278</td>
<td>1392</td>
<td>0</td>
<td>0</td>
<td>100</td>
</tr>
<tr>
<td>Manure or animal penning</td>
<td>764</td>
<td>597</td>
<td>3501</td>
<td>0</td>
<td>0</td>
<td>300</td>
</tr>
<tr>
<td>Hired equipment (tractors)</td>
<td>764</td>
<td>129</td>
<td>3259</td>
<td>0</td>
<td>0</td>
<td>0</td>
</tr>
<tr>
<td>Hired manual labor</td>
<td>764</td>
<td>5768</td>
<td>21951</td>
<td>0</td>
<td>0</td>
<td>13500</td>
</tr>
<tr>
<td>Hired oxen labor</td>
<td>764</td>
<td>499</td>
<td>2049</td>
<td>0</td>
<td>0</td>
<td>1200</td>
</tr>
<tr>
<td>Seeds</td>
<td>764</td>
<td>2890</td>
<td>3578</td>
<td>500</td>
<td>1800</td>
<td>6400</td>
</tr>
</tbody>
</table>

Note: All calculations are based on retrospective data regarding 2005 economic activity, and collected during household survey in 2006. N is the total number of observations, Mean, SD, p10, p50 and p90 correspond respectively to the mean, standard deviation, 10th, 50th, and 90th percentile of the distribution.

### Table 5: Credit: summary statistics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>p10</th>
<th>p50</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Total amount of loan active between September 2005 and September 2006</td>
<td>764</td>
<td>4839</td>
<td>37367</td>
<td>0</td>
<td>0</td>
<td>7000</td>
</tr>
<tr>
<td>R</td>
<td>68</td>
<td>30%</td>
<td>26%</td>
<td>6%</td>
<td>23%</td>
<td>65%</td>
</tr>
</tbody>
</table>

Note: N is the total number of observations, Mean, SD, p10, p50 and p90 correspond respectively to the mean, standard deviation, 10th, 50th, and 90th percentile of the distribution.

### Table 6: Total farm income: summary statistics

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>p10</th>
<th>p50</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>Farming income</td>
<td>764</td>
<td>40714</td>
<td>82699</td>
<td>1963</td>
<td>25491</td>
<td>82609</td>
</tr>
<tr>
<td>Revenue from crops and by-products sale</td>
<td>764</td>
<td>18771</td>
<td>39823</td>
<td>0</td>
<td>8000</td>
<td>41200</td>
</tr>
<tr>
<td>Value of own production</td>
<td>764</td>
<td>39524</td>
<td>78817</td>
<td>5781</td>
<td>21986</td>
<td>74569</td>
</tr>
</tbody>
</table>

Note: All calculations are based on retrospective data regarding 2005 economic activity, and collected during household survey in 2006. N is the total number of observations, Mean, SD, p10, p50 and p90 correspond respectively to the mean, standard deviation, 10th, 50th, and 90th percentile of the distribution.
Table 7: What affects the production of groundnut the most?

<table>
<thead>
<tr>
<th></th>
<th>N</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Rainfall</td>
<td>581</td>
<td>78%</td>
</tr>
<tr>
<td>Pests</td>
<td>68</td>
<td>9%</td>
</tr>
<tr>
<td>Damaged inputs</td>
<td>28</td>
<td>4%</td>
</tr>
<tr>
<td>Other</td>
<td>23</td>
<td>3%</td>
</tr>
<tr>
<td>Time and quality of soil preparation</td>
<td>22</td>
<td>3%</td>
</tr>
<tr>
<td>Price of inputs</td>
<td>14</td>
<td>2%</td>
</tr>
<tr>
<td>Time of planting</td>
<td>6</td>
<td>1%</td>
</tr>
<tr>
<td>Type of land</td>
<td>5</td>
<td>1%</td>
</tr>
<tr>
<td>Variety of seeds</td>
<td>2</td>
<td>0%</td>
</tr>
<tr>
<td>Total</td>
<td>749</td>
<td>100%</td>
</tr>
</tbody>
</table>
Table 8: Various measures of risk among farmers: summary statistics

<table>
<thead>
<tr>
<th>Risk factor</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>p10</th>
<th>p50</th>
<th>p90</th>
</tr>
</thead>
<tbody>
<tr>
<td>CRRA coefficient, $\rho$</td>
<td>764</td>
<td>2.67</td>
<td>3.25</td>
<td>0</td>
<td>0.56</td>
<td>8</td>
</tr>
<tr>
<td>Discount rate</td>
<td>764</td>
<td>0.54</td>
<td>1.56</td>
<td>0</td>
<td>0.25</td>
<td>0.75</td>
</tr>
<tr>
<td>Discount factor, $\beta$</td>
<td>764</td>
<td>0.76</td>
<td>0.18</td>
<td>0.57</td>
<td>0.8</td>
<td>1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Risk behavior</th>
<th>N</th>
<th>Mean</th>
<th>SD</th>
<th>Min</th>
<th>p50</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>On the face scale from 0 (“I always try to avoid taking risk”) to 10 (“I am fully prepared to take risks”). How would you rate your willingness to take risks in trying new crop varieties?</td>
<td>764</td>
<td>7.41</td>
<td>3.27</td>
<td>2</td>
<td>9</td>
<td>10</td>
</tr>
<tr>
<td>On a scale from 0 to 10, how trustworthy do you think are the insurance companies?</td>
<td>764</td>
<td>5.08</td>
<td>3.39</td>
<td>0</td>
<td>5</td>
<td>10</td>
</tr>
<tr>
<td>On a scale from 0 to 10, how trustworthy do you think are NASFAM, OIBM, and MRFC?</td>
<td>764</td>
<td>5.92</td>
<td>2.52</td>
<td>3</td>
<td>5.67</td>
<td>10</td>
</tr>
<tr>
<td>Did the household had to cut children’s meal due to lack of food in 2005? (Yes=1)</td>
<td>764</td>
<td>65%</td>
<td>0.48</td>
<td>0%</td>
<td>100%</td>
<td>100%</td>
</tr>
<tr>
<td>If there is a major drought this coming season, will your household face a food shortage? (Yes=1)</td>
<td>764</td>
<td>77%</td>
<td>0.42</td>
<td>0%</td>
<td>100%</td>
<td>100%</td>
</tr>
</tbody>
</table>

Note: N is the total number of observations, Mean, SD, p10, p50 and p90 correspond respectively to the mean, standard deviation, 10th, 50th, and 90th percentile of the distribution for the outcome of interest.
Table 9: What would you like to do if a reliable forecast said “Bad rains are more likely next season”?

<table>
<thead>
<tr>
<th>Action</th>
<th>N</th>
<th>Frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Select right crop variety</td>
<td>333</td>
<td>46%</td>
</tr>
<tr>
<td>Work harder on the field</td>
<td>199</td>
<td>27%</td>
</tr>
<tr>
<td>Grow more food crops</td>
<td>76</td>
<td>10%</td>
</tr>
<tr>
<td>Diversify income</td>
<td>48</td>
<td>7%</td>
</tr>
<tr>
<td>Grow more cash crops</td>
<td>15</td>
<td>2%</td>
</tr>
<tr>
<td>Use of irrigation</td>
<td>16</td>
<td>2%</td>
</tr>
<tr>
<td>Prepare soil and plant earlier</td>
<td>6</td>
<td>1%</td>
</tr>
<tr>
<td>Nothing</td>
<td>7</td>
<td>1%</td>
</tr>
<tr>
<td>Other</td>
<td>26</td>
<td>4%</td>
</tr>
<tr>
<td>Total</td>
<td>726</td>
<td>100%</td>
</tr>
</tbody>
</table>
References


