

The impact of weather insurance on consumption, investment, and welfare

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I develop and estimate a dynamic stochastic optimization model to assess the impact of weather insurance on the consumption, investment, and welfare of farmers in developing countries. Weather insurance has the potential to provide large welfare gains, equivalent to a permanent increase in consumption of almost 17%. Moreover, it can allow for the adoption of riskier but more productive seeds, further enhancing welfare. The interplay with other uninsured risks, the presence of liquidity constraints, basis risk, and loading factor on the insurance premium may account for the low take-up that is often empirically observed.

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JEL CLASSIFICATION. G22, O12, O13, O16, O33, Q14.

1. INTRODUCTION

Weather variations can have severe effects on the well-being of farmers in developing countries. Dercon (2002) finds that 78% of Ethiopian households suffered “hardship episodes” over the past 20 years as a result of harvest failures due to weather shocks. Similarly, Cole, Giné, Tobacman, Topalova, Townsend, and Vickery (2013) report that drought and weather risks in general are reported as the major source of adverse income shocks by almost 88% of rural Indian households in the state of Andhra Pradesh and Gujarat.¹

Weather shocks are particularly detrimental to farmers’ welfare because it is difficult to insure against them. As shown by Giné, Townsend, and Vickery (2007), weather shocks impact all households in the affected area and thus severely limit the effectiveness of informal risk-sharing networks.² The provision of weather insurance therefore has the potential to largely enhance farmers’ welfare by improving their ability to more effectively insure against risks associated with weather shocks. Based on this premise,

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¹The fact that farmers’ incomes depend strongly on good weather is also dramatically exemplified by the spike in the suicide rate recently observed after three consecutive years of droughts in Andhra Pradesh.

²The effectiveness of informal risk-sharing networks in buffering *idiosyncratic* shocks is documented in the seminal paper by Townsend (1994) and subsequent literature such as Fafchamps and Lund (2003), Gertler and Gruber (2002), and Angelucci and De Giorgi (2009).

more and more funds have been devoted to the design and promotion of weather insurance projects in recent years.³

Despite the many resources being allocated to weather insurance projects, however, there has been little research to quantify the potential benefits of this type of insurance. 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, past research casts doubts on 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 found a low take-up of weather insurance (for example, [Cole et al. \(2013\)](#), [Giné and Yang \(2009\)](#)).

In this paper, I construct and structurally estimate a dynamic stochastic model of farmers in developing countries to analyze the impact of weather insurance on their investment, consumption, and welfare. In each period, farmers decide how to allocate their resources between consumption and agricultural investment; this decision then determines their income in the next period. The return on investment is subject to both idiosyncratic productivity shocks and weather variations. Considering first the qualitative implications of the model, I show that the introduction of insurance has a priori uncertain implications for consumption and investment. This is because the presence of weather shocks has two counterbalancing effects on investment decisions. On the one hand, uncertainty in the rate of return deters investment; on the other hand, the presence of risk generates a precautionary motive that leads to extra investment. Therefore, whether the provision of insurance induces farmers to invest more or less depends on which of these two forces prevails.

To explore the quantitative implications of the model, I calibrate the distribution of weather shocks with agronomic data from Malawi and pin down the other parameters using Malawian household survey data from [Giné and Yang \(2009\)](#). In particular, I estimate the intertemporal discount factor and the coefficient of relative risk aversion based on questions of intertemporal preferences and attitudes toward risk. The survey also includes information regarding incomes and farm inputs that allows me to structurally estimate the remaining parameters of the model, such as the curvature of the agricultural production function and the standard deviation of the idiosyncratic shocks. The estimation is performed by matching the median and standard deviation of the income-to-investment ratio.

Using the estimated parameters, I proceed to assess the impact of weather insurance on consumption, investment, and welfare. I first consider a very simple setting,

³[Alderman and Haque \(2007\)](#) and [Hess, Skees, Stoppa, Barnett, and Nash \(2005\)](#) 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 4.5 million acres). Similarly, the Agricultural Insurance Company of India offers protection against excessive and deficit rainfall, humidity, and frost for more than 1 million Indian farmers.

assuming that weather insurance is actuarially fair and free from basis risk, and allowing farmers to buy the desired amount of insurance after observing the realization of their idiosyncratic productivity shock. Under these assumptions, farmers fully insure against weather shocks, and the estimated welfare gains therefore correspond to the *potential* gains that could be seized by providing an ideal insurance product. I find that the provision of weather insurance boosts consumption and reduces investment, as farmers' precautionary motives to overinvest weaken considerably as insurance reduces their risk. The associated welfare gains are quite large, equivalent to a permanent increase in consumption of 16.9%. Therefore, weather insurance has the potential to substantially enhance farmers' welfare.

However, the fact that weather insurance reduces investment leads to a gradual reduction in these welfare gains over time, since lower investment leads to lower future incomes. Interestingly, this is not necessarily the case once the model is extended to incorporate alternative investment options. For example, a major issue for farmers in developing countries is the decision to use traditional versus hybrid seeds. The latter have higher expected yields but may be more sensitive to weather variations and thus riskier. I show that in this setting, the provision of weather insurance involves an additional source of welfare gains because the elimination of weather risk allows farmers to adopt higher yield hybrid seeds, leading to higher productivity and higher incomes. Contrary to the case in which only one farming technology is available, this scenario (involving both weather insurance and improved seed varieties) involves a gradual increase in welfare gains over time.

Despite the large welfare gains predicted by the model, experimental evidence has often documented a surprisingly low take-up of weather insurance. To shed light on this issue, I relax the assumptions of actuarially fair insurance premium, no basis risk, no liquidity constraints, and the ability to buy weather insurance after observing the idiosyncratic productivity.⁴ If the price of weather insurance includes a risk premium or if the insurance payouts are not perfectly correlated with the impact of weather shocks on yields (basis risk), farmers would not fully insure. This is also the case if farmers have to purchase insurance before observing their idiosyncratic productivity shock or earning their farm income. Under these circumstances, the model predicts a much lower take-up and smaller welfare gains. However, it is interesting to note that even if the take-up is fairly low, the welfare gains are still relatively high, so that a low insurance take-up does not imply that the provision of weather insurance is of little value.

The paper is structured as follows. The model is presented in Section 2 and the estimation of the parameters is discussed in Section 3. Section 4 analyzes the impact of weather insurance on consumption, investment, and welfare, and Section 5 extends the model to incorporate the choice between hybrid and traditional seeds. Section 6 discusses the factors that hinder insurance take-up, and Section 7 concludes by summarizing the key findings.

⁴In general, issues of moral hazard and adverse selection also impair the effectiveness of insurance. Problems of asymmetric information are, however, not relevant in the case of weather insurance, since payments are conditional on weather realizations that are exogenous for the farmer and directly observed by the insurer through local weather stations.

2. MODEL

To analyze the effects of weather insurance on farmers' consumption, investment, and welfare, I construct a dynamic model of farmers in developing countries who face aggregate weather risks and idiosyncratic production shocks. I first present the model in the absence of weather insurance ("baseline" framework) and then consider how the optimization problem changes with the introduction of insurance ("insurance" framework).

2.1 Baseline framework

Farmers maximize the expected present discounted utility of consumption $\mathbb{E} \sum_{j=0}^{\infty} \beta^j u(c_{t+j})$, where $u(c) = \frac{c^{1-\rho}}{1-\rho}$ is a constant relative risk-aversion (CRRA) utility function with a coefficient of relative risk aversion ρ . In each period, they decide how to allocate their wealth w between consumption c and agricultural investment k , which generates income according to a production function with decreasing marginal returns. Agricultural income is also subject to both idiosyncratic productivity shocks ε and weather variations η .

Formally, farmers' optimization problem in the absence of weather insurance (labelled baseline framework) can be expressed as

$$V(w, \varepsilon) = \max_{k \geq 0} u(w - k) + \beta \mathbb{E} V[\mathcal{A} \varepsilon_i k^\alpha a^{1-\alpha} \eta, \varepsilon'_i],$$

where a is the land owned by each farmer and \mathcal{A} is the individual-specific time-invariant productivity. The idiosyncratic term ε is log normally distributed with mean 1 and variance σ_ε^2 . The distribution of the weather shock η is empirically calibrated as discussed in Section 3. I assume that farmers cannot adjust the amount of land a with which they are endowed.⁵

The first-order condition for the optimal level of agricultural investment is computed by equating the marginal utility of consumption today to the expected discounted marginal utility of consumption tomorrow. The optimization problem implies the existence of a well defined target level of wealth toward which farmers would converge if not hit by idiosyncratic or weather shock.⁶ I solve numerically for this target level of wealth and used it as the starting point to trace the impulse response function of the model to the introduction of weather insurance.

As in [Rosenzweig and Wolpin \(1993\)](#), I do not explicitly account for price variations caused by weather changes. The model is estimated using agronomic data from rural Malawi regarding the production of maize and groundnuts. Maize production is almost entirely (95%) consumed within the household. Additionally, since famine struck

⁵In developing countries, land trading is often limited by lack of property rights: indeed, according to survey data from [Giné and Yang \(2009\)](#), farmers claim ownership with deeds on only 25% of the land. Rental or sharecropping arrangements are only used on 2.3% and 0.2% of the total land, respectively. Moreover, it is unlikely that farmers would find it profitable to sell land when struck by an aggregate negative weather shock because weather shocks affect all farmers living nearby; thus the price of land would fall considerably if all farmers in the area try to sell land when facing a negative weather shock.

⁶There exists an interior solution for capital such that, at the steady state, households optimize their consumption decisions to equate the risk-adjusted marginal return from investment to the intertemporal discount rate, $\mathbb{E} \mathcal{A} \varepsilon_i \alpha k^{\alpha-1} a^{1-\alpha} \eta = \frac{1}{\beta}$.

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. A lower percentage of groundnut production (35%) is devoted to autoconsumption, but groundnuts account for a very small share of farm production, only about 15%. To the extent that price risk exists, it will play a similar role to a small amount of basis risk.

One possible concern with the model is that it may overstate the gains from weather insurance since farmers are not allowed to hold liquid assets or earn nonfarm income that could help them cope with weather shocks.⁷ Regarding liquid assets, the available household survey data show that farmers in Malawi have extremely low savings, which severely limits their ability to smooth consumption (Table 2). Cash at home and bank deposits—the two most popular saving instruments—correspond to only about 1% and 0.06% of farm income, respectively. These extremely low savings are likely the consequence of various episodes of high inflation that have generated strong negative real rates and made liquid holdings unattractive.⁸ In addition, savings in the form of nonliquid assets are of limited use in buffering consumption since it is unlikely that farmers can sell these assets among themselves when they are all hit by a weather negative shock, such as a drought, as documented by Dercon (2002). Regarding alternative sources of income, nonagricultural income is negligible, amounting to only about 0.09% of farm income (Table 3). A small number of farmers earn some agricultural income from on-farm work, but this source of income is likely to be heavily correlated with weather shocks since the demand for agricultural labor dramatically falls during episodes of severe weather.

2.2 Insurance framework

I introduce weather insurance by assuming that farmers have the opportunity to buy ι units of insurance, each of which pays $(1 - \eta)$ to offset any bad weather shocks. The optimization problem thus becomes $V(w, \varepsilon) = \max_{k \geq 0} u(w - k) + \beta \mathbb{E}V[\mathcal{A}\varepsilon_i k^\alpha a^{1-\alpha} \eta + \iota(1 - \eta) - \iota\mathcal{P}, \varepsilon'_i]$, where \mathcal{P} is the insurance premium. Note that the insurance payout is perfectly correlated with the weather shocks and that I am thus neglecting the possible presence of basis risk. In this section, I make two other simplifying assumptions that will be relaxed in Section 6. First, I assume that the insurance premium \mathcal{P} is actuarially fair, so that $\mathcal{P} = \int_0^1 (1 - \eta)f(\eta) d\eta$. Second, I allow farmers to observe the realization of their idiosyncratic shock ε before deciding how much insurance to buy.

The absence of basis risk, the actuarially fair premium, and the ability to observe the idiosyncratic shocks imply that farmers fully insure against weather shocks, so

⁷I also consider the possibility of investing in a riskless but less productive asset. Qualitatively, the main difference is with regard to the distribution of the welfare gains from weather insurance, which is no longer monotonically nondecreasing in wealth. Poorer, but not extremely poor, farmers gain more from the provision of insurance.

⁸In past years, Malawi has experienced high inflation rates of up to 73% in 2002 and equal to 18% in 2006 at the time of the Giné and Yang (2009) survey used in the estimation. Double-digit inflation leading to negative real rate of returns induced farmers in rural Tanzania to keep very little savings in cash or deposits (Dercon (1996)).

that $\iota = \mathcal{A}\varepsilon_i k^\alpha a^{1-\alpha}$. This formulation of the insurance problem allows us to quantify the *potential* welfare gains that could be seized by designing effective insurance products. The farmers' optimization problem (insurance framework) simply becomes $V(w, \varepsilon) = \max_{k \geq 0} u(w - k) + \beta \mathbb{E}V[\mathcal{A}\varepsilon_i k^\alpha a^{1-\alpha}(1 - \mathcal{P}), \varepsilon'_i]$, which differs from the baseline optimization problem since the weather shock has been replaced by its expected value $(1 - \mathcal{P}) = \int_0^1 \eta f(\eta) d\eta$.

Before proceeding with the estimation and quantitative analysis, I consider the qualitative implications of the model. Interestingly, the introduction of weather insurance has an ambiguous impact on investment that can either increase or decrease, depending on the parameter values. This is because, on one hand, weather shocks deter investment since they create uncertainty in the rate of return. But on the other hand, weather risk can stimulate investment through a precautionary motive as farmers overinvest so as to have enough income even in the case of negative weather shocks. Depending on the relative strength of these forces, investment can either increase or decrease when insurance removes weather risk.

To clarify with an example, Figure 1 traces the evolution of consumption and investment following the introduction of weather insurance under two different calibrations for the CRRA coefficient, which has a key impact on the investment response. More specifically, I set $\alpha = 0.7$, $\sigma_\varepsilon = 0.05$, and $\beta = 0.76$, let ρ be either 0.9 or 2, and initialize the impulse response functions at the target level of wealth without insurance, which remains constant until insurance is introduced at time t^* .⁹

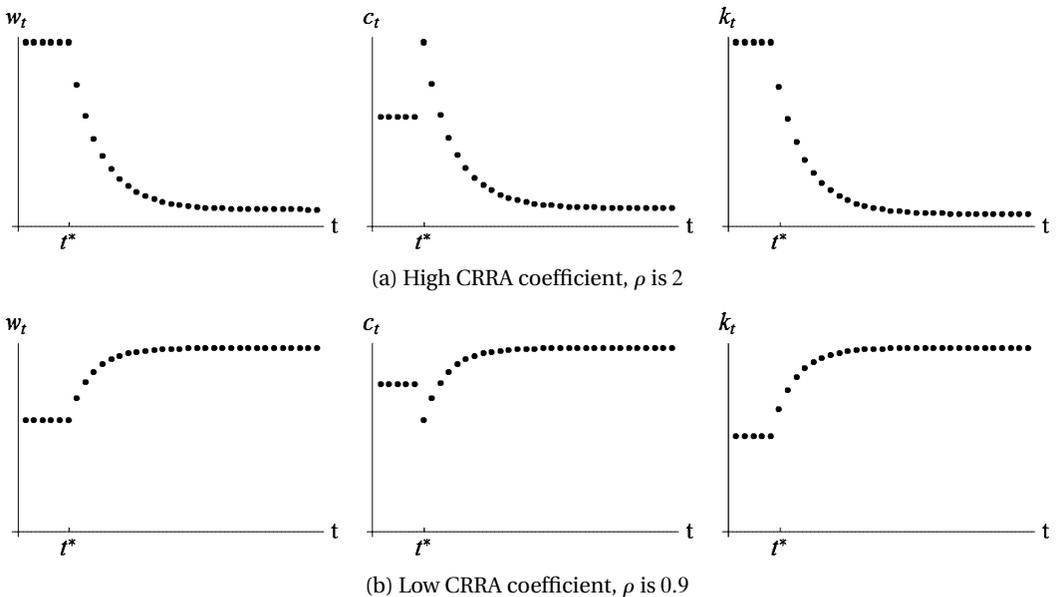


FIGURE 1. A priori unclear effect of the supply of weather insurance.

⁹I trace the impulse response functions by setting both idiosyncratic and aggregate shocks to their mean values. The actual shocks, however, are obviously present in the calculations of the policy functions.

Depending on the magnitude of the CRRA coefficient, the provision of weather insurance may either increase or decrease investment. More risk-averse individuals react to the provision of weather insurance by reducing the amount of capital invested given the weakening of precautionary motives (Figure 1(a)). Consequently, consumption jumps upward initially and then declines over time as the level of investment and 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.

3. CALIBRATION AND STRUCTURAL ESTIMATION

To analyze the quantitative implications of the model, I need to choose appropriate values for the CRRA coefficient ρ , the discount factor β , the capital share α , the variance of the idiosyncratic shock ε , and the parameters regarding the distribution of the aggregate weather shock η . As further discussed below, the production parameters \mathcal{A} and a act only as scaling factors; thus, I simply normalize them to 10 and 1, respectively.

To pin down these parameters, I use two data sources. First, I rely on agronomic data elaborated by the crop water satisfaction analysis (CWSA) module to estimate the weather shocks η . The CWSA module estimates the impact of rainfall variations on farmers' yields that, combined with the rainfall probability distribution, approximate the frequency and size of η .¹⁰ The covariant shock takes the value between 0 and 1, where 0 corresponds to the most disruptive weather shock. The crop model captures shocks due to both excess and lack of rainfall; thus, in case of either a devastating drought or flood, η would be equal to 0.

The rest of the parameters are pinned down using household survey data collected by Giné and Yang (2009).¹¹ About 770 maize and groundnut farmers in Malawi were interviewed in September 2006, gathering information on demographic and economic characteristics as well as on attitudes toward risk.¹² The latter set of questions allows us to pin down the coefficient of relative risk aversion ρ and the discount factor β , which are estimated to be, respectively, 2.67 and 0.76, using the answers to questions regarding the choice of gambles and the timing of lottery payments.¹³

The remaining parameters α and σ_ε cannot be directly pinned down; therefore, I structurally estimate them in the context of my model. The estimation is performed by

¹⁰Further details on how the CWSA module is constructed and the data it requires are available in Appendix A.

¹¹The household survey was fielded only before the randomized experiment, when farmers did not have access to weather insurance.

¹²The survey also asked farmers about the most serious risks they face. Weather shocks are clearly extremely important, since a lack of rainfall constitutes the main threat to groundnut production. Consistent with the model, farmers are also subject to idiosyncratic shocks, with pest infestation being the (distant) second most cited source of problems. Variations in input prices are a major concern for fewer than 2% of farmers.

¹³The specific questions and the calibration techniques are presented in Appendix A.

minimizing the distance between the median and the standard deviation of the income-to-capital ratio w/k generated by the model with their empirical counterparts.¹⁴ Since the survey data were collected when farmers had no access to weather insurance, the estimation is performed using the model without insurance (baseline framework). Invested capital k from the survey data is computed by summing all expenditures on farm inputs (irrigation, fertilizers, chemical pesticides, manure, or animal penning), rented equipment (such as tractors), hired manual labor, hired oxen labor, and seeds.¹⁵ Farmers' income, which in the model simply corresponds to the beginning of next-period wealth, 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.¹⁶

The curvature of the production function α is essentially identified by the median of the income-to-capital ratio. To understand why this is so, it is useful to think about a simplified version of the model without investment risk. The Euler equation would require $\alpha k^{\alpha-1} = \frac{1}{\beta}$, leading to a steady state capital level $k^* = (\frac{1}{\alpha\beta})^{1/(\alpha-1)}$. This implies a steady state income-to-capital ratio equal to $\frac{1}{\alpha\beta}$, which clearly allows us to identify α for a given calibrated value for β . To show that this intuition is still valid in the presence of investment risk, I solve the baseline model under two different levels of α , with $\alpha_2 > \alpha_1$, and show that they imply different equilibrium income-to-capital ratios. Figure 2 plots the production functions under each level of α and shows the equilibrium levels of capital on the horizontal axis.¹⁷ We observe that, as in the version of the model without in-

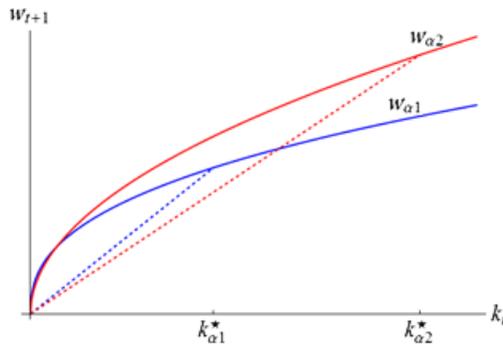


FIGURE 2. Identification strategy for the share of capital α .

¹⁴I target the median rather than the mean since it is robust to the presence of outliers. The estimate of the capital share is unaffected by the presence of liquidity constraints (further discussed in Section 6) as long as the farmer with the median investment-to-income ratio is not liquidity constrained.

¹⁵Table 4 in Appendix C presents the summary statistics for farmers' total expenditures and the separate components.

¹⁶The value of internal consumption is also accounted for since, in the model, w is the wealth at the beginning of the period before consumption takes place. 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.

¹⁷The equilibrium capital levels are defined as the investment levels that farmers choose at the target level of wealth. As defined in Section 2.1, the target level of wealth is the amount of wealth that remains

vestment risk, an increase in α leads to a reduction in the equilibrium income-to-capital ratio.

The standard deviation of the idiosyncratic shock σ_ε is instead identified by the standard deviation of the income-to-capital ratio. The intuition is straightforward with a higher variance of the idiosyncratic shocks leading to a wider dispersion in wealth levels and in the associated income-to-capital ratio.¹⁸

To briefly describe the details of the estimation procedure, I take a pair of values for α and σ_ε , and using the policy functions solved under the baseline model, simulate the consumption and investment responses of 1000 agents subject to idiosyncratic and weather shocks over time. The realization of weather shocks mimics the specific weather conditions in Malawi in the years leading up to the survey. At the end of each simulation, I compute the median and standard deviation of income-to-capital ratio. This procedure is repeated to search for the values of α and σ_ε that minimize the gap between the empirical and simulated statistics.

Figure 3 shows the contour plot for the joint estimation of the parameters. The level curves represent the parameters' combinations that generate an equal deviation between simulated and actual statistics, while the darker areas indicate lower distance. We

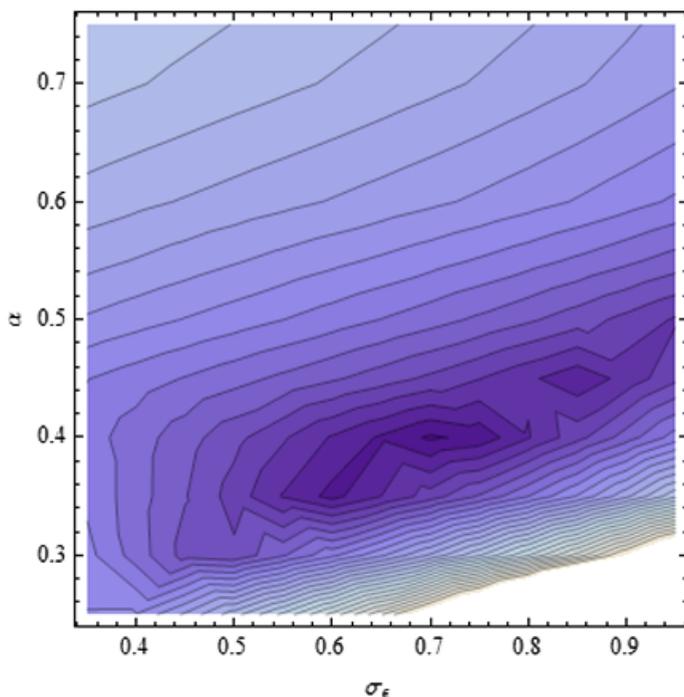


FIGURE 3. Identification strategy for both the share of capital α and the standard deviation (SD) of the idiosyncratic shocks σ_ε .

constant if the farmer is not hit by shocks. This is also very close to the average level of wealth obtained from simulating the model.

¹⁸Possible measurement error in the data may lead to overstatement of the volatility of idiosyncratic shocks unless capital and income are characterized by identical multiplicative measurement error.

TABLE 1. Model parameters.

<i>Calibrated Parameters</i>		
Distribution of weather shock η_t	Empirical distribution from the CWSA module	
Discount factor β	0.76	Parameters calibrated using Giné and Yang (2009) survey data
CRRRA coefficient ρ	2.67	
<i>Estimated Parameters</i>		
	Point Estimate	Standard Deviation
Capital share α	0.39	(0.0010)
SD idiosyncratic shock σ_ε	0.54	(0.0075)

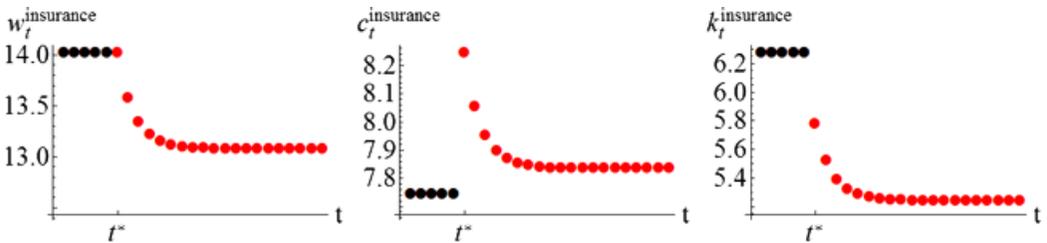


FIGURE 4. Impulse response functions of wealth, consumption, and investment to the introduction of weather insurance.

observe that there is a well defined region where the simulated and actual statistics are closer to each other. The values for α and σ_ε that lead to the minimum gap are, respectively, 0.39 and 0.54. The standard errors for these point estimates are computed using a bootstrap procedure, repeating the estimation 500 times over a sample of 500 observations chosen with replacement from the survey data set. The standard errors and all the other parameters are reported in Table 1.

4. WELFARE GAINS FROM WEATHER INSURANCE

Using the calibrated and estimated parameters, I first consider the impact of weather insurance on consumption and investment. Figure 4 traces the impulse response functions triggered by the provision of actuarially fair insurance as described in Section 2.2. Starting from the target level of wealth and setting the idiosyncratic and weather shocks to their mean values, I observe that the introduction of insurance at time t^* determines a sudden increase in consumption and reduction in investment.¹⁹ As discussed in Section 2.2, this implies that the availability of insurance weakens the precautionary motives that lead to overinvestment. The reduction in investment lowers future income, generating a gradual decline in consumption. However, even in the long run, households are able to sustain a higher level of consumption than is possible in the absence of

¹⁹This result holds at any level of wealth, as evident from the change in the policy functions for consumption and investment with the introduction of insurance. These plots are available from the author upon request.

insurance. The reduction in investment leads to an increase in the marginal productivity of capital, allowing farmers to consume more from each unit of farm income.²⁰ The predicted reduction in investment has very important implications. It may be tempting to argue that insurance is welfare-enhancing as long as it allows farmers to increase investment. However, the model shows that this conclusion is erroneous, since insurance may actually allow farmers to reduce the excessive investment they previously had to engage in as a protection against negative weather shocks.

Moving to the quantification of the welfare gains from weather insurance, I express these as the permanent increase in consumption that would make a farmer without insurance as well off as a farmer with insurance. Formally, this corresponds to the χ_t such that $\mathbb{E}\sum_{j=0}^{\infty} \beta^j u(c_{i,t+j}^{\text{baseline}}(1 + \chi_t)) = \mathbb{E}\sum_{j=0}^{\infty} \beta^j u(c_{i,t+j}^{\text{insurance}})$. Given the homotheticity of the CRRA utility function, the percentage of the increase in consumption can also be expressed more clearly as $(1 + \chi_t)^{1-\rho} V^{\text{baseline}}(w_t) = V^{\text{insurance}}(w_t)$, that is, $\chi_t = (\frac{V^{\text{insurance}}(w_t)}{V^{\text{baseline}}(w_t)})^{1/(1-\rho)} - 1$.

Figure 5(a) shows the welfare gains as a function of the wealth level. First, I observe that these gains are quite substantial, being equal to a permanent increase in consumption of 16.9 percentage points for a farmer at the target level of wealth, identified by the vertical dashed line. Second, it is interesting to note that the gains are higher for wealthier farmers. This might seem somewhat counterintuitive since the poorest farmers should be the ones who suffer the most from negative shocks; however, weather insurance provides protection against investment risk and thus is more beneficial for those farmers with higher investment.

The dynamic structure of the model provides a further interesting insight regarding the evolution of welfare gains over time. By reducing investment, the introduction of weather insurance leads to a gradual reduction in wealth. As shown in Figure 5(b), this

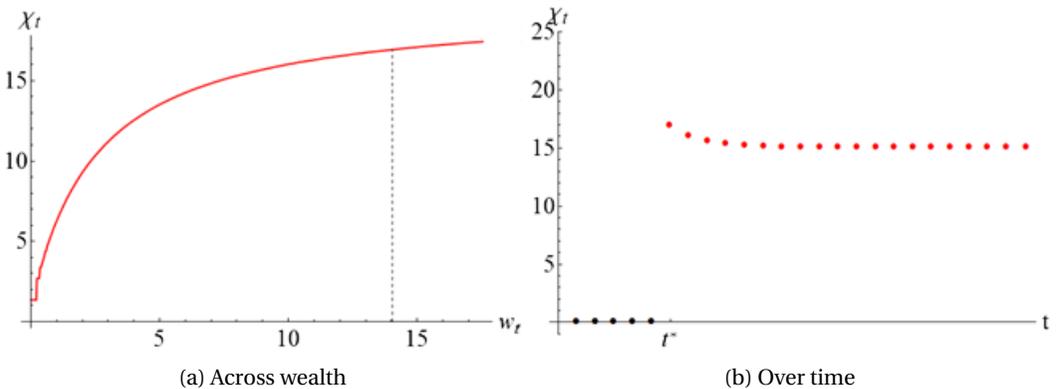


FIGURE 5. Welfare gains from weather insurance.

²⁰Notice that in the qualitative analysis of the model in Figure 1 (top middle plot), the ultimate level of consumption was lower than that without insurance, following a reduction in investment. This is because different values of α were used, implying a lower response in the marginal productivity of capital.

implies that welfare gains tend to decline over time. In the next section, I show that by extending the model to introduce several investment options with a different rate–return combination this does not necessarily have to be the case.

5. ADOPTION OF RISKIER BUT MORE PRODUCTIVE TECHNOLOGY

The analysis has so far revealed that weather insurance can lead to large welfare gains that shrink over time due to a reduction in investment. We now extend the model to show that weather insurance can actually stimulate investment by inducing farmers to choose riskier but more productive investment technologies.

As documented by the agricultural and development literature, their inability to protect themselves against weather risks forces farmers in developing countries to make conservative investment choices; this lack of choices can perpetuate poverty. [Fafchamps and Kurosaki \(2002\)](#) and [Dercon and Christiaensen \(2011\)](#) claim that rare but severe weather shocks may induce farmers to underinvest in high return, but also highly volatile projects. Similarly, [Chetty and Looney \(2006\)](#) point out that small consumption fluctuations should not lead one to underestimate the need for insurance; rather, these fluctuations may indicate that, because of their limited ability to cope with risk, farmers invest in low-volatility, low-return activities.

A particularly relevant issue for farmers in Malawi is the decision to use hybrid seeds instead of traditional varieties. The former have a higher average yield but are also more sensitive to weather shocks.²¹ To incorporate these alternative varieties of seeds, I modify the dynamic stochastic optimization problem in the absence of insurance as

$$V(w, \varepsilon) = \max_{k_t, l_t, k_h \geq 0} u(w - k_t - k_h) + \beta \mathbb{E}V[\mathcal{A}_h \varepsilon_i k_h^\alpha (1 - l_t)^{1-\alpha} \eta_h + \mathcal{A}_t \varepsilon_i k_t^\alpha l_t^{1-\alpha} \eta_t, \varepsilon'_i],$$

where \mathcal{A}_h and \mathcal{A}_t are the total factor productivities, and η_h and η_t are the aggregate weather shocks, respectively, for hybrid and traditional crops. Hybrid crops are on average more productive than traditional crops; that is, $\mathcal{A}_h > \mathcal{A}_t \frac{\mathbb{E}\eta_t}{\mathbb{E}\eta_h}$, but their yields are also more volatile, $\text{Var}(\eta_h) > \text{Var}(\eta_t)$. Each crop is produced using its technology-specific capital k_h or k_t , and labor l_h or l_t as input. The total amount of labor, $l_h + l_t$, is normalized to 1.²²

²¹[Sintowe \(2006\)](#) reports that local Malawian crops perform better than their hybrid counterparts (i.e., are potentially more productive) during times of weather stress. Furthermore, as argued by [Duflo, Kremer, and Robinson \(2008\)](#), so as to maximize hybrid yields, farmers need to apply fertilizer (an expensive farm input with volatile returns) 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 the seed and the fertilizer is completely lost.

²²Note that when farmers invest in only one crop, all their labor is allocated to the production of that crop. This is because labor was not explicitly included as a choice variable in the previous version of the model with only one investment technology.

Let us consider how the optimization problem changes if farmers are given the opportunity to purchase actuarially fair weather insurance with no basis risk for both crops after they observe their idiosyncratic shock. Under these conditions, farmers would again fully insure against weather shocks, so that the optimization problem becomes

$$V(w, \varepsilon) = \max_{k_t, l_t, k_h \geq 0} u(w - k_t - k_h) + \beta \mathbb{E}V[\mathcal{A}_h \varepsilon_i k_h^\alpha (1 - l_t)^{1-\alpha} (1 - \mathcal{P}_h) + \mathcal{A}_t \varepsilon_i k_t^\alpha l_t^{1-\alpha} (1 - \mathcal{P}_t), \varepsilon'_i],$$

where \mathcal{P}_h and \mathcal{P}_t correspond to the insurance premia for the traditional and hybrid crops, which are defined as $\mathcal{P}_h = \int_0^1 (1 - \eta_h) f_h(\eta_h) d\eta_h$ and $\mathcal{P}_t = \int_0^1 (1 - \eta_t) f_t(\eta_t) d\eta_t$. The optimization problem can be further simplified by considering that with weather insurance, hybrid seeds become as risky as traditional ones. Therefore, farmers entirely invest in hybrid seeds, simplifying the optimization problem to

$$V(w, \varepsilon) = \max_{k_h \geq 0} u(w - k_h) + \beta \mathbb{E}V[\mathcal{A}_h \varepsilon_i k_h^\alpha (1 - \mathcal{P}_h), \varepsilon'_i].$$

The distinction between hybrid and traditional seeds requires us to calibrate the respective distribution of weather shocks and average productivity. We use again the CWSA designed by Osgood, McLaurin, Carriquiry, Mishra, Fiondella, Hansen, Peterson, and Ward (2007) to derive the empirical distributions of the weather shocks η_t and η_h . The yields from hybrid crops are much more volatile in response to weather fluctuations, with the standard deviation of η_h being more than twice as large as that of η_t ($\sigma_{\eta_h} = 0.23$, $\sigma_{\eta_t} = 0.1$). Regarding the relative productivities, I set $\mathcal{A}_h = 1.5 \mathcal{A}_t \frac{\mathbb{E}\eta_t}{\mathbb{E}\eta_h}$ since, according to Malawi Department Meteorological Services (2007), hybrid crops are 50% more productive than traditional ones.

Let us now reconsider the impact of weather insurance on consumption, investment, and welfare when farmers can plant both traditional and hybrid seeds. In the absence of insurance, farmers invest in both crops and the proportion of capital invested in hybrid seeds is an increasing function of wealth, ranging from 40% for poorer farmers to about 60% at the target level of wealth.²³ Figure 6 shows that when weather insurance becomes available, farmers invest entirely in hybrid crops.²⁴ The level of consumption increases on impact, and the total level of investment ($k_t + k_h$) falls moderately. However, the higher investment return boosts income so that wealth increases over time, which is different from the result seen in the model with only one crop.

²³This implication of the model is consistent with the empirical evidence. Rosenzweig and Binswanger (1993) show that poorer households adopt less efficient and less productive techniques so as to minimize weather risks. Similar conclusions are reached by Zimmerman and Carter (2003), who show that optimal portfolio strategies are a bifurcate function of wealth, with poorer households investing 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. Interestingly, the model shows that the existence of initial fixed costs is not a necessary condition to account for the empirical evidence.

²⁴This is consistent with the empirical evidence in Cole, Giné, and Vickery (2011).

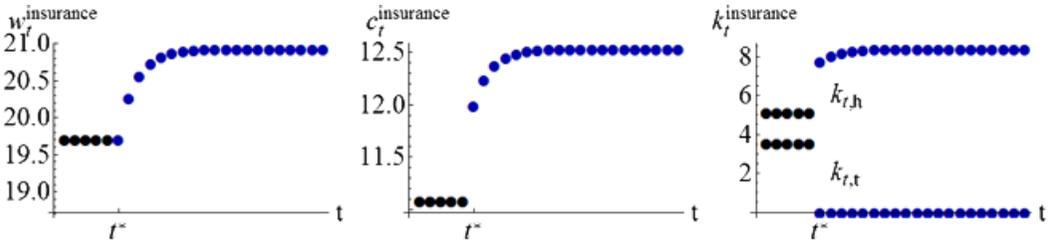


FIGURE 6. Dynamic responses of wealth, consumption, and investment to the introduction of weather insurance when farmers plant hybrid and traditional crops.

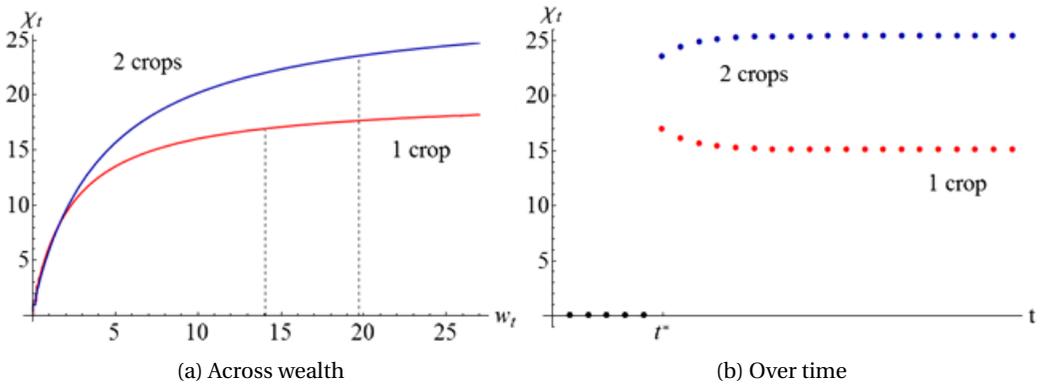


FIGURE 7. Welfare gains from weather insurance when farmers plant hybrid and traditional crops.

Regarding welfare implications, the gains from weather insurance are considerably larger when I allow for this adjustment in the investment composition. As can be seen in Figure 7(a), the welfare gains are higher at any level of wealth, being equivalent to a permanent increase in consumption of 23.4% at the target level of wealth in the model with two crops. Furthermore, Figure 7(b) shows that the gains are now increasing over time, essentially reflecting the increase in wealth.

These large welfare gains contrast with [Rosenzweig and Wolpin \(1993\)](#), who argue that the introduction of actuarially fair weather insurance is associated with only negligible welfare gains. Three elements may explain these contrasting results. First, I explore an additional channel through which weather insurance can improve welfare, by extending the analysis to the production of two crops and introducing the possibility for farmers to adopt a more productive but riskier technology. Second, I modify the structure of the production shocks and no longer impose a minimum consumption floor that would automatically reduce the need for insurance. Third, I bundle all the expenditure on farming inputs so as to improve the precision of the structural parameters' estimates as the level of heterogeneous variation in the data increases.

6. FACTORS HINDERING TAKE-UP

Despite the large potential welfare gains from weather insurance predicted by the model, experimental evidence has often documented a low take-up (see, for instance, Cole et al. (2013) and Giné and Yang (2009)). In this section, I consider four factors that may be responsible for low take-up. For each of them, I present the related changes in the theoretical framework, discuss the calibration of the new parameters, and assess the impact on insurance take-up and welfare gains.

First, the insurance premium may not be actuarially fair but may include a loading factor to cover administrative costs or risk premia. As a result, the optimization problem becomes $V(w, \varepsilon) = \max_{k \geq 0} u(w - k) + \beta \mathbb{E}V[\mathcal{A}\varepsilon_i k^\alpha a_i^{1-\alpha} \eta + \iota(1 - \eta) - \iota\mathcal{P}(1 + \theta), \varepsilon'_i]$, where the loading factor θ inflates the actuarially fair premium \mathcal{P} .

Second, the insurance payouts may not perfectly compensate for the actual losses experienced by farmers due to the presence of basis risk. Farmers may live relatively far from weather stations and thus experience precipitation different from that recorded. Furthermore, differences in soil composition, exposure to sunlight, and slope of the plot can change the impact of rainfall on yields and thus prevent the insurer from accurately predicting the losses suffered by farmers. The insurance payouts are no longer perfectly correlated with the weather shocks due to the presence of the error term ξ , which captures basis risk. Hence the optimization problem can be written as $V(w, \varepsilon) = \max_{k \geq 0} u(w - k) + \beta \mathbb{E}V[\mathcal{A}\varepsilon_i k^\alpha a_i^{1-\alpha} \eta + \iota(1 - \eta)\xi - \iota\mathcal{P}, \varepsilon'_i]$, where ξ is assumed to be log normally distributed with mean 1 and variance σ_ξ^2 .

Third, I have so far assumed that the purchase of weather insurance takes place after the realization of uninsurable idiosyncratic shocks. The desired take-up, however, is lower if farmers are instead offered insurance before observing their idiosyncratic shocks. For example, a farmer may be reluctant to insure against weather shocks if he is obligated to pay the insurance premium even if he later falls sick and is unable to harvest. Farmers now have to decide how many units of insurance to purchase ι , conditional only on their wealth level w and, thus, before the realization of the idiosyncratic shocks ε , that is, they solve $V(w) = \max_{k \geq 0} u(w - k) + \beta \mathbb{E}V[\mathcal{A}\varepsilon_i k^\alpha a_i^{1-\alpha} \eta + \iota(1 - \eta) - \iota\mathcal{P}]$.

Fourth, I have not yet accounted for the presence of liquidity constraints. Thus far I have assumed that farmers pay the insurance premium after they earn their farm income, so as to quantify all the *potential* benefits from insurance.²⁵ I now relax this assumption and let households pay the premium in advance. To isolate the role of liquidity constraints, I assume that farmers buy insurance at the same time they make their investment and consumption decisions, but after they observe the realization of their idiosyncratic shock. Their optimization problem becomes $V(w, \varepsilon) = \max_{k, \iota \geq 0} u(w - k - \iota\mathcal{P}) + \beta \mathbb{E}V[\mathcal{A}\varepsilon_i k^\alpha a_i^{1-\alpha} \eta + \iota\varepsilon_i(1 - \eta), \varepsilon'_i]$.

²⁵Technically I have implicitly imposed that farmers could pay for the insurance premium through an interest-free loan, as U.S. farmers are able to do (Liu and Myers (2012)).

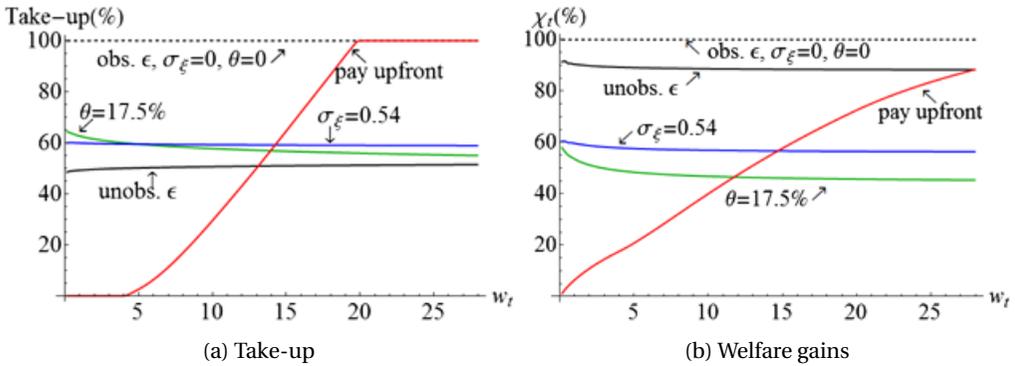


FIGURE 8. Weather insurance with loading factor (θ), basis risk (ξ), unobservable idiosyncratic shocks, and upfront payment of the premium.

To assess the role of each factor, the values of θ and σ_ξ need to be determined. I set the loading factor θ equal to 17.5%, which corresponds to the government tax levied on the provision of insurance in the [Giné and Yang \(2009\)](#) randomized experiment. Calibrating the extent of basis risk is less clear-cut; for the purpose of this exercise, I simply set the standard deviation of σ_ξ equal to the standard deviations of the idiosyncratic shocks, 0.54. This leads to a correlation between the insurance payments and actual losses of 0.74.

Figure 8(a) shows how the take-up rate varies depending on the features of the weather insurance contract sold. I measure take-up as the ratio $\frac{t}{Ak^{\alpha}a^{1-\alpha}}$, that is, the proportion of agricultural income that farmers decide to insure against weather shocks. Each factor by itself can reduce take-up rates quite substantially. Not surprisingly, the largest drop in take-up is observed when poorer farmers have to pay upfront for the insurance premium. As farmers become richer, they can afford to buy as much insurance as needed to fully insure their investment (100% take-up). Interestingly, insurance take-up is nearly halved when farmers observe the realization of their idiosyncratic shocks after purchasing insurance.

The consequences for welfare are shown in Figure 8(b), which plots the gains from the provision of insurance as a percentage of those derived in Section 4 with an actuarially fair premium paid after the harvest, no basis risk, and observable shocks at the time of the insurance decision. The percentage reduction in take-up due to the loading factor and basis risk is mirrored by an (almost) equivalent fall in welfare gains of about 50%. When idiosyncratic shocks are unobservable, the impact on welfare gains is much smaller since they shrink by only 10%. Even poorer farmers are able to improve their welfare when forced to pay upfront.²⁶ They gain access to insurance and no longer need to overinvest to smooth their consumption. It is important to notice that the gains from the provision of insurance are still far from negligible, despite their contraction.

²⁶Qualitatively similar results are obtained in case less expensive, catastrophic weather insurance is offered.

Therefore, an interesting insight of the model is that even with a fairly low insurance take-up, the benefits from weather insurance remain substantial.

7. 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. The potential gains from the provision of weather insurance can be very large, equivalent to almost a 17% permanent increase in consumption. The dynamic nature of the model reveals that these benefits can, however, decline over time because the introduction of weather insurance can lead to a decline in investment. This occurs because weather insurance reduces the precautionary motives that stimulate farmers' savings and investment.

Welfare gains can be larger if farmers have access to various investment opportunities that differ in their risk–return characteristics. In an extension of the model that allows farmers to choose between traditional seeds and riskier but higher return hybrid seeds, the provision of insurance induces farmers to shift to hybrid seeds. This further boosts their welfare gains and leads to higher welfare over time because of the increase in farmers' incomes.

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. The model reveals that the desired take-up level can be significantly reduced by the presence of liquidity constraints, by a loading factor on the insurance premium, or by basis risk, which leads to insurance payouts that are not perfectly correlated with losses. Furthermore, the lower take-up may also be due to the interplay of other idiosyncratic shocks that are not yet realized at the time of the insurance purchase. Allowing farmers to pay the insurance premium after harvest, pricing the insurance premium at its actuarially fair rate, improving the measurement of weather conditions and their impact on agricultural yields, and conditioning the insurance payouts on idiosyncratic shocks as well as weather shocks are thus important avenues to further improve the effectiveness of weather insurance.

APPENDIX A: PARAMETER CALIBRATION: FURTHER DETAILS

Coefficient of relative risk aversion ρ

I calibrate the coefficient of constant relative risk aversion ρ and the value for the discount factor β using the data with regard to attitudes toward risk based on a series of hypothetical questions. The calculation of the coefficient of relative risk aversion ρ 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 the coin lands on heads and the money shown under the WHITE area if the coin 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 ρ and then take the average of the median value for each interval, as done by De Mel, McKenzie, and Woodruff (2008).

Discount factor β

The discount factor β is constructed with the answers to the following two questions:

1. Imagine that you bought a lottery ticket and you have just won. The prize is MWK1000 (1000 Malawian Kwachas). You can get the MWK1000 now for sure. However, if you are willing to wait 30 days, you can get more. What option do you prefer?

- (a) $\left\{ \begin{array}{l} \text{MWK1000 prize today;} \\ \text{MWK1250 prize 30 days from now.} \end{array} \right.$
- (b) $\left\{ \begin{array}{l} \text{MWK1000 prize today;} \\ \text{MWK1500 prize 30 days from now.} \end{array} \right.$
- (c) $\left\{ \begin{array}{l} \text{MWK1000 prize today;} \\ \text{MWK1750 prize 30 days from now.} \end{array} \right.$

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 β 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 (2011), 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 questions, 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 take 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 β . To assess the relevance of this issue, in Appendix B, I show how welfare gains are affected by a change in the point estimate of β .

Weather shock η

As anticipated in Section 3, the distribution of the weather shock is derived from the crop water satisfaction analysis (CWSA) module. The CWSA module was designed by the International Research Institute for Climate and Society at Columbia University. It combines soil, crop phenotype, weather data bases, and management options to simulate crops’ reaction to a water deficit. In particular regarding weather data, it uses the daily time series for the rainfall level from 1961 to 2006 from each of the five villages where the surveyed farmers live, as well as evaporation data regarding the amount of soil moisture needed to optimize production specific to the four Malawian regions analyzed in Giné

and Yang (2009). The simulations are based on the United Nations Food and Agricultural Organization (FAO) estimates for the parameters that regulate each crop's growth cycle (the crop coefficients KC), its reactivity to water shortages during the different phases of this cycle (the varying yield response factors KY), and its sensitivity to evapotranspiration (seasonal KY). Finally, using the 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 a farmer's ability to forecast the beginning of the rainy season, which would instead be captured in the idiosyncratic productivity term.²⁷

APPENDIX B: SENSITIVITY ANALYSIS

In this section, I explore the sensitivity of the welfare gains to the key parameter 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 α , σ_ε , β , \mathcal{R} , and ρ , holding constant the other parameters. Results are reported in Figure 9. Figures 9(a)–(d) show that welfare gains from weather insurance increase in α , σ_ε , β , and ρ . In reference to the possible concern expressed in Appendix A that the discount factor β is somewhat lower than other values used in the literature, the sensitivity plot shows that a higher β would imply even higher welfare gains. Figure 9(d) shows that, intuitively, gains are strongly increasing in the relative risk-aversion coefficient ρ . 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 2), it is still highly welfare enhancing, $\chi_t = 4.8\%$. The sensitivity analysis for the risk preferences parameters plays an important role given that the choice-over-lotteries question to elicit β and ρ was not incentivized. As such, the estimates of the risk preferences parameters may be biased by measurement error.²⁸ Specifically, I consider seven insurance contracts with different premium–coverage combinations. The first contract provides coverage only against the worst weather shock. Subsequent contracts become more expensive as coverage is progressively extended.²⁹ Figure 9(e) shows that as the insurance offers more coverage, the level of the welfare gains that can be achieved increases.

B.1 *Departing from the optimal insurance contract*

I also 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 discussed in Section 5

²⁷The estimates of the weather shock are robust to alternative crop models; the CWSA estimates are preferable since this crop model was precisely calibrated for the farmers interviewed by Giné and Yang (2009).

²⁸More accurate estimates of β and ρ could be derived using the convex time budget approach by Andreoni and Sprenger (2012). Unfortunately the survey design precludes this option.

²⁹The coverage thresholds are based on a discretization of the distribution of the weather shock in bins with equal probability.

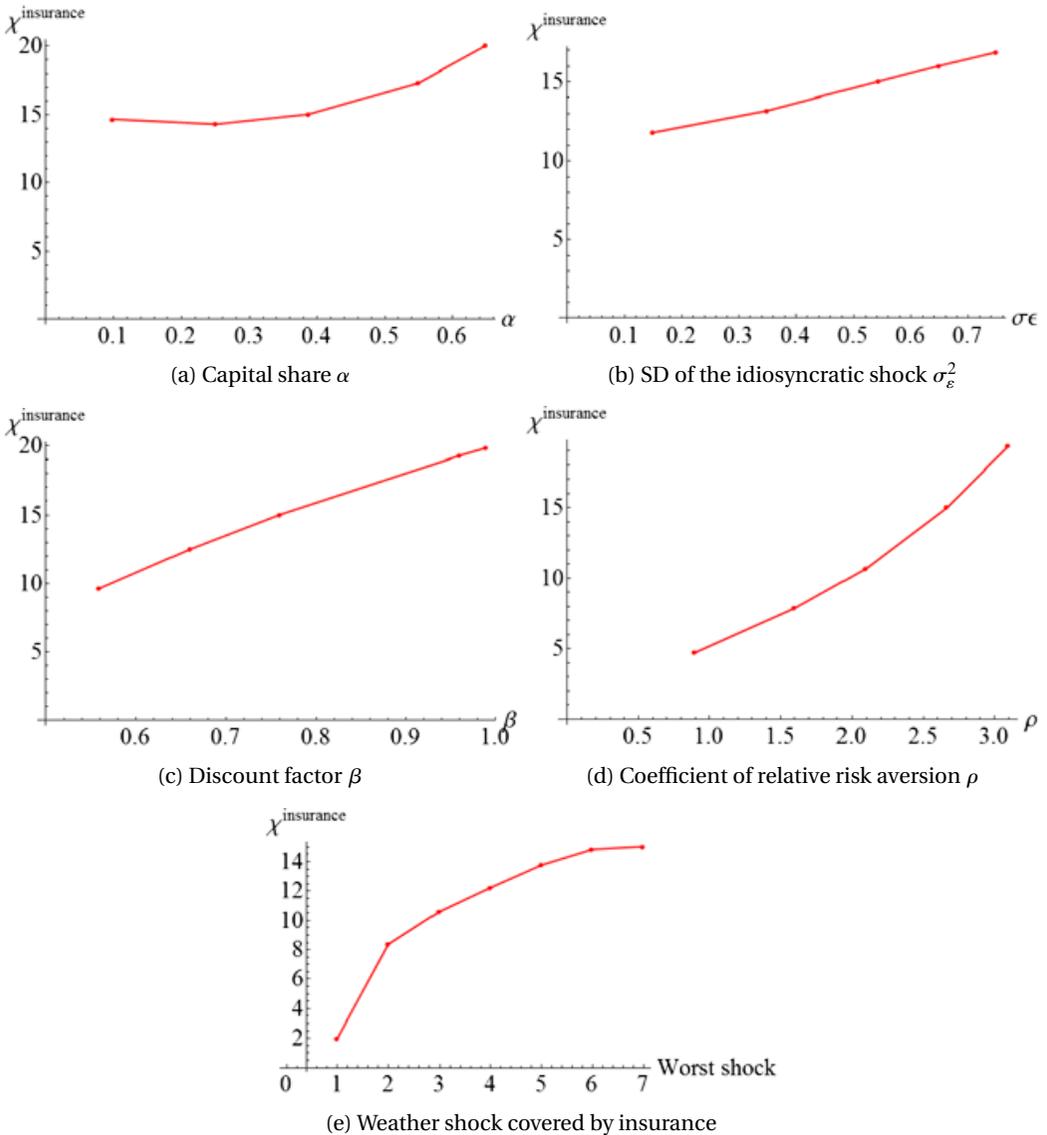


FIGURE 9. Sensitivity analysis of welfare gains with respect to the model parameters.

depend on the chosen calibration.³⁰ Figure 10 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 (Figure 10(a)) or loading factor (Figure 10(b)). 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.

³⁰The literature also considers other factors to explain the low take-up of insurance. For example, if farmers have time-inconsistent preferences, they may not be capable of setting aside the funds required to pay for the insurance premium.

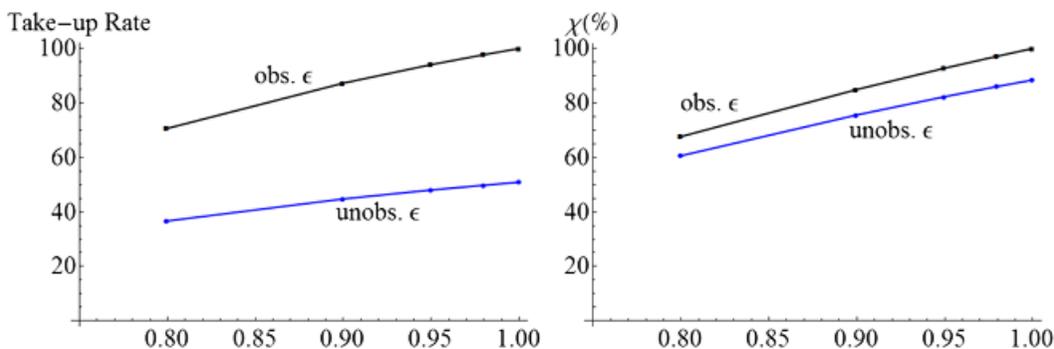
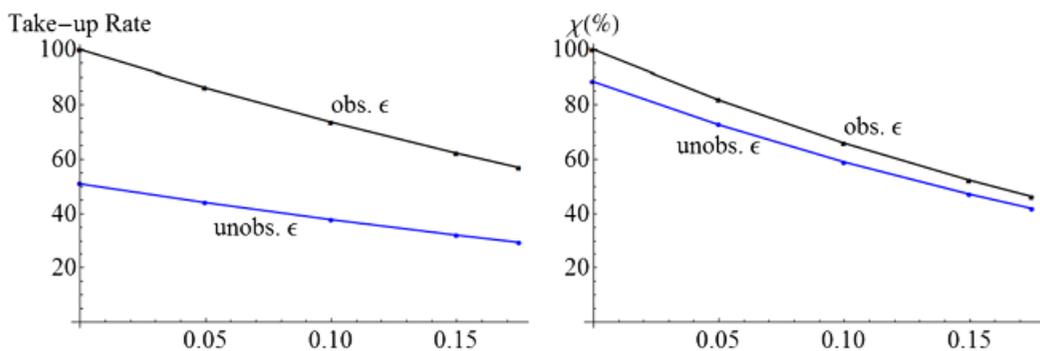
(a) Basis risk measured by the correlation between insurance payment and farmer losses, $\sigma_\xi > 0$ (b) Risk premium, $\theta > 0$

FIGURE 10. Sensitivity analysis of welfare gains and weather insurance take-up with respect to the model parameters.

APPENDIX C: TABLES

TABLE 2. Savings: Summary statistics.

	<i>N</i>	Mean	SD	p10	p50	p90
<i>In 2006</i>						
Saving deposits with any bank	151	14,719	24,378	1500	6000	35,000
Cash at home	486	5379	9782	400	2000	12,000
Non-livestock assets (seeds, bike, etc.)	402	22,252	60,103	2000	9000	50,000
Club or other group revolving fund	49	3902	6069	400	1000	12,000
Livestock	764	24,670	62,612	0	6350	55,000
<i>In 2005</i>						
Saving deposits with any bank	154	22,152	39,150	1000	12,000	50,000
Cash at home	476	7906	11,204	500	5000	20,000
Non-livestock assets (seeds, bike, etc.)	396	20,341	59,822	2000	7000	39,000
Club or other group revolving fund	45	3674	6052	0	900	15,000

Note: All calculations are based on retrospective data regarding 2005 and collected during household survey in 2006. The variable *N* indicates the total number of households that declare they have savings; Mean, SD, p10, p50, and p90 correspond, respectively, to the mean, standard deviation, and 10th, 50th, and 90th percentiles of the distribution.

TABLE 3. Nonfarm income: Summary statistics.

	<i>N</i>	Mean	SD	p10	p50	p90
Wages from agricultural labor	240	6259	51,936	250	1000	5500
Wages from nonagricultural sector	104	23,591	51,404	500	5000	78,000
Wages from public works program	102	2484	3264	225	2000	4820
Migration income/remittance	66	3626	3540	600	2050	7800
Benefits from government scheme	67	3673	3375	500	3000	8500
Pensions	13	30,335	99,163	257	2000	15,600
Other income sources (such as gambling)	36	6539	11,574	300	3000	12,000

Note: All calculations are based on retrospective data regarding 2005 economic activity, and collected during household survey in 2006. The variable *N* indicates the total number of household declaring receiving income from sources other than own farm work; Mean, SD, p10, p50, and p90 correspond, respectively, to the mean, standard deviation, and 10th, 50th, and 90th percentiles of the distribution.

TABLE 4. Total expenditure on farm inputs: Summary statistics.

	<i>N</i>	Mean	SD	p10	p50	p90
Farm inputs	764	17,580	36,256	1850	7200	39,700
Irrigation	764	122	1223	0	0	0
Fertilizer	764	7297	16,414	0	2350	16,150
Chemical insecticides	764	278	1392	0	0	100
Manure or animal penning	764	597	3501	0	0	300
Hired equipment (tractors)	764	129	3259	0	0	0
Hired manual labor	764	5768	21,951	0	0	13,500
Hired oxen labor	764	499	2049	0	0	1200
Seeds	764	2890	3578	500	1800	6400

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

TABLE 5. Total farm income: Summary statistics.

	<i>N</i>	Mean	SD	p10	p50	p90
Farming income	764	40,714	82,699	1963	25,491	82,609
Revenue from crops and by-products sale	764	18,771	39,823	0	8000	41,200
Value of own production	764	39,524	78,817	5781	21,986	74,569

Note: All calculations are based on retrospective data regarding 2005 economic activity and collected during the household survey in 2006. *N* indicates the total number of household that declare they have savings; Mean, SD, p10, p50, and p90 correspond, respectively, to the mean, standard deviation, and 10th, 50th, and 90th percentiles of the distribution.

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