How Does Risk Management Influence Production Decisions? Evidence from a Field Experiment

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Weather is a key source of income risk, especially in emerging market economies. This paper uses a randomized controlled trial involving Indian farmers to study how an innovative rainfall insurance product affects production decisions. We find that insurance provision induces farmers to invest more in higher-return but rainfall-sensitive cash crops, particularly among educated farmers. This shift in behavior occurs ex ante, when realized monsoon rainfall is still uncertain. Our results suggest that financial innovation can mitigate the real effects of uninsured production risk. (*JEL* C93, D13, D14, G22, G32, O16, Q14)

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Small entrepreneurial firms around the world are exposed to a wide range of income risks, including recessions, demand shifts, technology shocks, weather, and natural disasters. Reflecting these risks, around one-third of US business establishments fail within two years (Puri and Zarutskie 2012). Risks associated with entrepreneurship may be even greater in volatile emerging market economies. For a risk-averse individual, these uninsured risks can be a significant disincentive to engage in entrepreneurial activity (Moskowitz and Vissing-Jørgensen 2002; Banerjee and Newman 1993).

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This paper studies a financial innovation designed to mitigate income risk among a sample of Indian farmers located in a semi-arid region where variation in monsoon rainfall is the dominant source of production and income risk. In this context, we study the effects on behavior of a rainfall index insurance policy, which partially insures against a poor monsoon by providing a payout contingent on low measured local rainfall.

Our goal is to estimate the effects of the rainfall insurance on real production and investment decisions by farmers. Given that the decision to purchase insurance is typically endogenous, we use a randomized controlled trial (RCT) to elicit the causal effects of insurance provision. At the start of the monsoon, a randomly selected subset of farmers (the "treatment group") is provided with 10 rainfall insurance policies with a combined market value of approximately 1,000 Indian rupees (equivalent to ca. $20 US at the time of our study). This represents a significant amount of coverage for our sample; the maximum insurance payout of 10,000 rupees (Rs.) is equivalent to about 90% of median household savings. We then study how this insurance provision influences subsequent production decisions such as crop choice and usage of agricultural inputs, compared to a control group promised a *fixed* payment equal to the estimated actuarial value of the insurance.

We find that while insurance provision has little effect on total agricultural investments, it significantly induces farmers to invest more in riskier production activities. In particular, treated farmers increase production of the main cash crops grown in our study areas, castor and groundnut. These crops produce higher expected returns but are also more sensitive to deficient rainfall. We find that insured farmers are more likely to plant these two cash crops, sow more land with them, and devote a larger amount of agricultural inputs to them, relative to uninsured farmers. Quantitatively, the fraction of farmers planting cash crops is 6 percentage points higher for the treatment group (p-value = 0.041), a 12 percent increase relative to the control group, about half of whom planted cash crops in the year of our study. The evidence suggests the impact of insurance is primarily on the extensive margin: it has large effects on the decision to sow cash crops, but little effect among the subset of farmers with the highest cash crop investments.

These results imply that farmers are underinsured and suggest that financial innovation that helps diversify weather risk can promote entrepreneurial production and risk-taking. We next test whether the average treatment effect varies by household characteristics and find that it is much larger for educated farmers. In contrast, the treatment effect does not vary systematically with other characteristics including farmer wealth, age, knowledge of insurance, trust in the insurance provider, or past experience with the insurance product.

To investigate the role of education in more detail, we first confirm that the effect is robust to a variety of specification changes and the inclusion of a battery of additional interaction effects, including a measure of cognitive ability.

Examining triple-differences, we show that the treatment effect of insurance on investment is concentrated among farmers who are both educated and expect highly variable yields. This perhaps suggests that educated farmers may be better able to think through the complex interactions between production risk, insurance and agricultural decisions.

Using data on the timing of agricultural decisions, we find that the effects of insurance provision on production decisions occur ex ante, prior to the end of the insurance coverage period, when the insurance payout and monsoon rainfall are still uncertain. We also conducted a second follow-up survey in the following year, after insurance payouts were disbursed, to study how insurance payouts were ultimately spent by farmers. While the statistical power of this analysis is relatively low, our results suggest that payouts were mainly saved for the next monsoon or used to pay down high interest-rate sources of credit.

Although insurance is a key function of the global financial system, we have only a partial understanding of how insurance provision causally influences real economic behavior and risk-taking. This study is among the first in a small body of recent research which uses a RCT approach to study the causal relationship between insurance and agricultural decisions. Karlan et al. (2014) randomly allocate cash grants and discounted insurance, or both, offered by a nongovernment organization to farmers in Ghana, finding that while both increase investment, a given subsidy directed towards insurance induces a larger increase in investment than an equivalent credit subsidy. Mobarak and Rosenzweig (2013) conduct a randomized evaluation that uses subsidies to induce households to purchase insurance against late monsoon arrival. While their focus is the interaction between insurance demand and informal risk-sharing, they also find evidence that insured households plant riskier varieties of rice, although planting may happen after knowledge of the payout. In a related study, Cai et al. (2015) find evidence from China that hog insurance increases investment in hogs. Finally, Emerick et al. (2016) study the introduction of a drought-resistant rice variety that both increases average yields and reduces the sensitivity of yields to weather, finding that the rice variety increases land cultivated, fertilizer usage, and the use of a more labor intensive planting method.

Several features distinguish our paper from this complementary literature. First, our design allows us to study how insurance affects the timing of decisions and to distinguish clearly between ex ante effects of insurance (effects on behavior during the insurance coverage period) and ex post effects due to the receipt of insurance payouts or the anticipation of future payouts. Second, we equate the wealth effect across experimental arms by compensating the control group so that differences in behavior between the treatment and control group are due to the state-contingent nature of the insurance. Third, we explore heterogeneity in treatment effects, documenting that behavior change is present primarily among those with relatively higher levels of education, and take care to rule out that this effect is driven by other factors, such as wealth or cognitive ability. Finally, we present evidence on how insurance payouts are used. Taken together, this nascent literature demonstrates in a variety of institutional and economic settings that access to insurance leads to an increase in risky production activities.

More generally, our analysis contributes to the vast literature on risk, growth, and technology adoption in emerging market economies (e.g., Acemoglu and Zilibotti 1997; King and Levine 1993; Banerjee and Newman 1993; Rosenzweig and Binswanger 1993). While technological improvements from the "Green Revolution" such as high-yield crops and chemical fertilizer have dramatically increased global agricultural productivity, traditional practices still prevail in many areas (Duflo, Kremer and Robinson 2008; Hazell 2009; Foster and Rosenzweig 2010). Our evidence suggests that limited insurance against production risk is one reason why firms limit investments that produce high expected returns but involve risk. Correspondingly, financial innovation that "completes" missing markets, like the insurance policy we study, may boost risk-taking and technology adoption. This channel may account for part of the link between finance and growth identified in prior research (Levine 2005; Beck, Levine and Loayza 2000).[1]

Our evidence is also related to the financial economics literature on the link between finance and entrepreneurial activity. This literature tends to focus on developed economies and on credit rather than insurance (e.g., Adelino, Schoar and Severino 2015; Hurst and Lusardi 2004; Black and Strahan 2002). More closely related, Fan and White (2003) find evidence of greater business ownership associated with the option to declare bankruptcy, a procedure that allows entrepreneurs to shield future income and some assets from creditors, limiting the downside risk of entrepreneurship. Recent research by Campello et al. (2011) and Pérez-González and Yun (2013) finds causal evidence that risk management affects investment and firm value, although these papers study large, financially sophisticated corporations rather than the sole proprietor farmers considered here.

Finally, the household finance literature is increasingly examining the possibility that households may not make optimal decisions relating to complex financial products (e.g., Campbell 2006). Our finding that changes in behavior are concentrated among educated farmers contributes to a growing body of evidence that education affects financial decision-making (e.g., Cole, Paulson and Shastry 2014).

1. Background and experimental design

Consumption risk-sharing, though surprisingly effective in mitigating nonsystematic income shocks (Cochrane 1991; Townsend 1994), has been

[1] Our analysis is also related to research studying the effects of climate change on agricultural productivity. Guiteras (2009) estimates that predicted climate change from 2010–2039 will reduce crop yields by 4.5-9 percent. While rainfall insurance cannot, of course, affect the climate, it may enable farmers to continue producing risky crops in the face of greater climate variability, mitigating the real impact of climate change.

found to be incomplete, particularly for spatially correlated shocks such as weather. Droughts, for example, have significant negative effects on economic well-being and health for rural households in India and other emerging market economies, suggesting that the risk of drought is underinsured (Burgess et al. 2013; Maccini and Yang 2009; Jayachandran 2006; Rose 1999; see Cole et al. 2013, for further references).

When consumption cannot be fully insured against drought or other income risks, individuals may respond by smoothing income ex ante, selecting production and investment activities that generate less volatile income at the cost of lower average income (Morduch 1995; Gollier and Pratt 1996; Walker and Ryan 1990). Corporate finance research makes an analogous prediction for firms: in the presence of financial constraints, a firm facing non-diversifiable risks may invest less in additional risky projects, particularly when the project return is positively correlated with existing risk exposures (Froot and Stein 1998). Income-smoothing tactics for farmers include intercropping by drought tolerance, spatial separation of plots, shifting the timing or staggering of planting, moisture conservation measures such as bunds, furrows and irrigation, and diversifying income between agricultural and non-agricultural sources. Several papers find suggestive evidence of costly income smoothing by farmers in developing countries (Rosenzweig and Stark 1989; Morduch 1995; Dercon 1998; Dercon and Christiaensen 2011).[2]

The key hypothesis tested in this paper is that the provision of insurance against rainfall risk will induce households to allocate more resources to higher-risk, higher-yield investment and production activities. To fix ideas, Section OA1 of the Online Appendix to this paper illustrates this hypothesis using a simple model in which a risk averse farmer chooses between two production activities: one safe, the other higher-yielding but risky. Insurance against production risk induces farmers to allocate more resources to the high-risk activity. While our model uses a simple CARA-normal setup, this basic prediction will apply to nearly any model with risk-averse agents, incomplete markets and production risk.

We test this hypothesis in a setting where firms face a dominant, exogenous source of production risk: variation in local monsoon rainfall. Rainfall is cited as the most important source of risk by 89% of farmers in our study areas. Although these local rainfall shocks are approximately uncorrelated with aggregate asset returns, farmers in our sample have a large, non-diversified exposure to local

[2] Rosenzweig and Stark find that farmers with more volatile profits are more likely to have a wage-earning household member. Morduch suggests that households close to subsistence devote a larger share of land to safer crop varieties. Dercon finds Tanzanian farmers with more liquid assets engage in higher-risk agricultural activities. Dercon and Christiaensen find that fertilizer purchases are lower among poorer Ethiopian households, in part due to their lesser ability to smooth shocks ex post. Rosenzweig and Binswanger (1993) estimate that a one standard deviation increase in the variability of monsoon onset would, through reduced risk-taking, reduce agricultural profits by 15 percent for the median farmer. An advantage of the present study relative to this prior research is that our RCT design exogenously varies the farmer's exposure to rainfall risk, ameliorating concerns about omitted variables.

weather risk. Recognizing the importance of rainfall risk, Indian insurers have recently developed innovative retail index insurance products designed to pay out when realized monsoon rainfall is poor. We study a particular policy designed and underwritten by ICICI Lombard, a large, privately-owned, national Indian insurance firm. Our analysis builds on a series of experiments and surveys that we have conducted since 2004 in Andhra Pradesh, India (Cole et al. 2013; Giné et al. 2008). This previous work focuses on the determinants of rainfall insurance demand and the barriers to widespread insurance uptake, rather than the impact of insurance on behavior.[3]

1.1 Crop choice and risk-taking

Our empirical analysis focuses on the allocation of agricultural inputs by farmers across crop types with different levels of risk. During the main cropping season (June to November) in our study areas, farmers grow a variety of cash and subsistence crops that vary by sensitivity to low rainfall. The primary cash crops grown in the study areas are castor and groundnut, two rain-fed oilseeds, as well as paddy, which is almost exclusively irrigated and thus less subject to rainfall risk (84% of paddy plots in our empirical sample are irrigated). The main subsistence crops grown in the area are sorghum and legumes (red gram, pigeon pea, and, to a lesser extent, green gram).

Cultivation costs for the main cash crops exceed those of subsistence crops and range between Rs. 5,000 and Rs. 9,000 per hectare ($94 to $168 US) if the recommended amounts of organic and inorganic fertilizer are applied.[4] Based on the local District Handbook of Statistics, average yields for castor are 600 Kg per hectare if fertilizer is used, which would generate Rs. 10,896 in revenue at 2009 prices. Groundnut yields are 540 Kg per hectare with fertilizer, corresponding to Rs. 11,702. Sorghum yields with fertilizer are 700 Kg per hectare or Rs. 4,788, and red gram yields are 300 Kg or Rs. 5,791. Thus, expected profits for castor and groundnut are indeed higher at Rs. 2,771 and Rs. 2,951 compared to sorghum (negative Rs. 212) and red gram (Rs. 141). In terms of water requirements, castor grown in Mahbubnagar under rain-fed conditions requires 625 mm of accumulated rainfall over the season if sown around the normal planting date, while groundnut in Anantapur requires 533 mm. Red gram requires a similar amount of accumulated rainfall, 523 mm, but, in contrast, sorghum only requires 376 mm, and green gram 278 mm.[5]

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[3] Although some of our earlier research also adopts a field experimental approach (Giné and Yang 2009; Cole et al. 2013), uptake has been too limited to allow an assessment of the impact of insurance on investment decisions. Two related laboratory experiments conducted by Lybbert et al. (2010) and Hill and Viceisza (2012) suggest that, over time, subjects learn about insurance and change behavior accordingly.

[4] Input recommendations (used to calculate 2009 production costs per hectare for castor, groundnut, sorghum, and red and green grams) come from the University of Agricultural Sciences in Bangalore (1999).

[5] These water requirement statistics are drawn from personal communication from Dr. Bodapati Rao and Dr. Vijay Kumar, Principal Scientists at the Indian Central Research Institute for Dryland Agriculture (CRIDA).

To summarize, castor and groundnut are more profitable on average than other crops grown in our study areas but have higher water requirements and therefore are more sensitive to drought.

1.2 Product description

The rainfall insurance policies offered in this study are an example of "index insurance," that is, a contract whose payouts are linked to a publicly observable index like rainfall, temperature or a commodity price. Unlike traditional insurance products, index insurance is not generally subject to moral hazard or adverse selection problems, because payouts are linked to an exogenous, publicly observable variable, in this case, rainfall measured at a local rain gauge. Index insurance also involves lower administrative costs because no claims verification process is required. However, rainfall insurance only covers rainfall-related losses and may entail significant basis risk, especially if the household is located too far from the relevant weather reference station.[6]

Information frictions and high transaction costs have limited the commercial success of agricultural insurance. Insurance companies have initiated a number of index insurance pilots in recent years in the hope of developing a financially sustainable product that farmers will buy (World Bank 2005; Skees 2008). Today, rainfall insurance is one of the core product offerings of Indian agricultural insurance providers, with over 10 million farmers covered by index policies. Clarke et al. (2012) and Giné et al. (2012) provide sales data and non-technical overviews of this market as well as further institutional details.

For the ICICI Lombard policies we study, payoffs are calculated based on measured rainfall at a nearby government rainfall station or an automated rain gauge operated by a third-party vendor. ICICI Lombard offers separate policies for three different contiguous phases of the monsoon, of 35-45 days in length, corresponding to sowing, flowering, and harvest. This study offered only Phase I policies, which cover the first and most critical period of the monsoon.

The start date of the policy is defined as the first date at which cumulative rainfall since June 1 reaches 50 mm. The start date defaults to July 1 if June rainfall is below 50mm. Payouts are determined based on cumulative rainfall during the 35 days following the start date. The policy pays out if cumulative rainfall during this coverage period is below a threshold known as the "strike", designed to approximate the minimum quantity of rainfall required for successful crop growth. Payouts are linear in the rainfall deficit relative to the exit or are equal to a fixed maximum amount of Rs. 1000 per policy if rainfall is below a second, lower threshold called the "exit."

As an example, Figure 1 plots cumulative measured rainfall for the insurance policy indexed to rainfall at the Naryanpet weather station. The two dotted

[6] In our study, villages are generally located within 10 km of the reference weather station. Given the relatively flat terrain, basis risk may be relatively low for our sample, although we do not have data to test this directly.

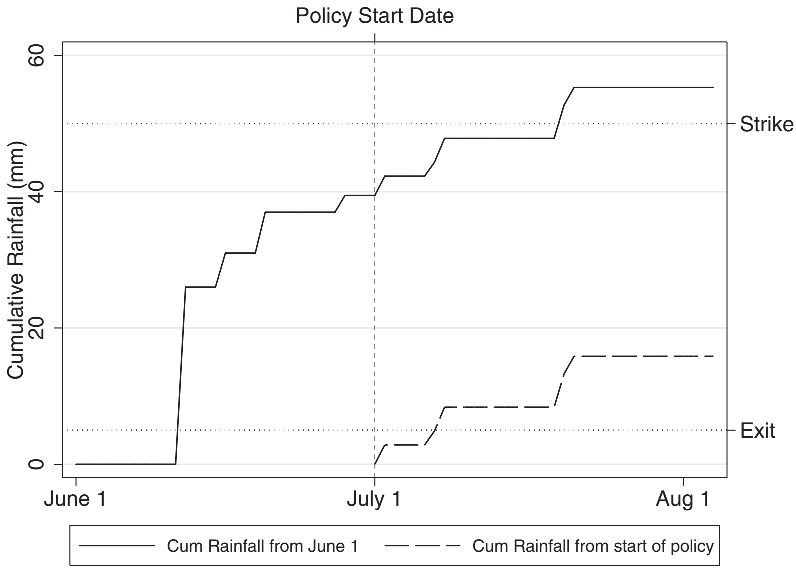

Figure 1
Example of Calculation of Rainfall Insurance Payout
Chart plots cumulative rainfall and rainfall insurance policy parameters for the policy indexed to the Naryanpet weather station.

horizontal lines represent the strike (top) and exit (bottom) levels specified in the policy. As one can see, realized rainfall was low in June, and cumulative rainfall did not reach the trigger of 50 mm. Thus, the 35 day policy coverage period started automatically on July 1. Cumulative rainfall then quickly crossed the exit (5mm) level but only reached 16 mm during the coverage period, well below the strike of 50mm. Each policy paid out Rs. 10 for each millimeter of the rainfall shortfall, or Rs. 10 x (50 – 16) = Rs. 340. This led to a total payout of Rs. 3,400 per farmer, since each treated farmer received ten policies.

Payouts are linked to rainfall measured at a nearby gauge, and treated farmers in our study received policies linked to one of five weather stations, depending on their village. Because the 2009 monsoon turned out to be significantly below average, three of these five policies provided positive payouts *ex post*, with one policy providing the maximum payout of Rs. 1,000 per policy, amounting to a total payout of Rs. 10,000 for each treated farmer. See Section 2 for a table of all the realized payouts.

1.3 The insurance experiment

Our sample consists of 1,479 farmers drawn from 45 villages in two semi-arid districts of southern India, Mahbubnagar in the state of Telangana

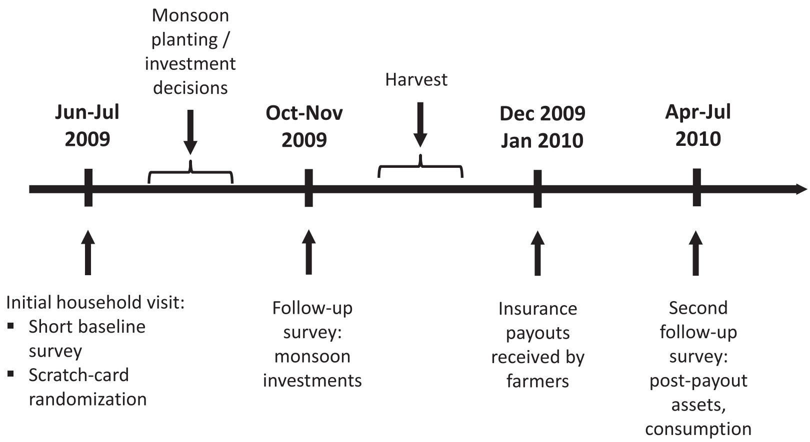

Figure 2
Timeline

and Anantapur in the state of Andhra Pradesh.[7] Two-thirds of the sample participated in previous surveys and field experiments we conducted on rainfall insurance; these were originally selected via a stratified random sample of land-owning farmers in 37 study villages in 2004 (see Giné et al. 2008, for details). To improve statistical power for this study, an additional five hundred households were drawn from these 37 villages as well as 8 nearby villages.

Figure 2 presents the timeline of events. Each farmer received a home visit from a member of a trained team of enumerators from the agricultural research organization ICRISAT between June 4 and July 13, 2009, coinciding with the onset of the 2009 monsoon season.[8] During the visit, the enumerator first conducted a short baseline survey, collecting demographic data and other information. They then explained the recommended fertilizer dosages for castor and groundnut, the two main rain-fed cash crops in the area, as well as the concept of insurance, and gave specific details about the policies offered by ICICI Lombard.

The farmer then received a scratch card (similar to the format of a scratch-off lottery ticket sold in the United States), revealing treatment assignment. The key treatment for the purposes of this paper is the assignment of the farmer to either an insurance group (treatment) or a control group. Farmers in the treatment

[7] Both districts were part of Andhra Pradesh at the time of the study; Telangana is a new state formed in 2014.

[8] Although we planned to distribute all insurance policies before the start of the insurance coverage period, delays in the shipping of policy certificates from ICICI headquarters in Mumbai resulted in 40 percent of the initial visits occurring on or after the policy activation date. Distribution occurred close to the start of the activation period in these cases, however, within five days on average, and only six percent of farmers had started planting by the time of the initial household visit and insurance assignment. The small amount of monsoon investments occurring before the distribution of insurance may mean that our results are slightly attenuated relative to the case where policies were distributed earlier, as earlier distribution would have given farmers more time to adjust behavior in response to receiving insurance coverage.

group received a certificate for 10 Phase-I weather insurance policies, similar to those sold in the region in previous years. “Control” farmers received a post-dated check for Rs. 200, equal to our estimate of the actuarially fair value of these 10 policies based on calculations using historical rainfall data.[9] This check could be cashed at the local branch of BASIX, the microfinance institution that sells ICICI Lombard rainfall insurance in our study villages.

The control group payment was provided to ensure that differences in behavior between the insurance and control groups reflect the state-contingent nature of the insurance, rather than a wealth effect. The insurance has the same expected value as the fixed payment received by the control group; the key difference is that the realized insurance payout is *contingent* on low realized rainfall. By design, the date when the check could be cashed also coincided with the expected timing of insurance payouts. This was to ensure that there were no differences in behavior between the treatment and control groups induced by earlier relaxation of liquidity constraints in one group compared to the other.

A second independent treatment, also provided via the scratch card, involved coupons for discounts on locally appropriate inorganic fertilizer (DAP in Anantapur, NP fertilizer in Mahbubnagar). Unfortunately the implementation of this treatment was largely unsuccessful, due to operational difficulties and the fact that the subsidies did not substantially affect fertilizer purchase behavior.[10] For that reason, we do not study it here, although we always control for the household’s fertilizer discount treatment status in our empirical analysis.[11]

Treatments were assigned randomly and independently across households. The use of scratch cards ensured that neither the respondent nor the enumerator had prior information about the household’s treatment status. Farmers also had the option to purchase additional insurance policies from BASIX, although few did so in practice.

In October and November 2009, after the growing season, the ICRISAT team revisited each farmer to conduct a follow-up survey, collecting information on agricultural investments and production decisions during the monsoon as well as asset data (e.g., livestock, and financial assets such as savings, loans, and insurance), risk-coping behavior, additional demographic information, and

9 Actuarial values are estimated using historical rainfall data from two Indian Meteorological Department (IMD) weather stations, one in each district, using the approach described in Giné et al. (2008). Historical rainfall data from the other three weather stations are not available because these gauges are maintained by a private vendor rather than the IMD and were only recently installed. The market price of ten insurance policies in our study areas ranges from Rs. 800 to Rs. 1100, significantly exceeding our estimate of average actuarial value. This high markup likely reflects the administration and transaction costs of offering insurance; it is also inclusive of taxes and a loading factor paid to the sales agent. In previous work, we argue that high transaction costs and prices represent one of several barriers to higher index insurance adoption (Cole et al. 2013).

10 The number of subsidized fertilizer bags was calibrated to fertilizer usage from a survey conducted in 2006. According to that survey, 70 percent of farmers in Mahbubnagar and 34 percent in Anantapur had used fertilizer, and users generally purchased at most two bags. However, follow-up data collected in November 2009 revealed significantly higher fertilizer usage than suggested by the earlier survey.

11 In practice, our results are almost identical whether or not we control for the fertilizer treatments, not surprisingly given that the two treatments are statistically independent by design.

attitudes and expectations regarding weather and insurance payouts. Although payouts had not been made by the time of the follow-up survey, because of the poor monsoon in 2009, 93% of the farmers in the treated group reported in the follow-up survey that they expected to receive a payout. Roughly the same percentage expected final crop yields to be below average.

Payouts to the insurance and control group were made in December 2009 and January 2010. This timing is well after one might have expected, given that policies indicate a settlement date of "thirty days after the data release by data provider and verified by Insurer." However, the timing was relatively consistent with previous years. The long timeframe reflected both slow release of rainfall data and slow processing by ICICI Lombard.

In mid-2010, we conducted a second follow-up survey to measure how realized insurance payouts were used by farmers. Although not the focus of this paper, our analysis of these data is summarized briefly in Section 3.G and discussed in more detail in Section OA2 of the Online Appendix.

2. Summary Statistics

Table 1 reports baseline summary statistics about farmers' household characteristics, education, insurance knowledge, trust, expectations, credit and assets (panels A-D), and statistics on agricultural investments during the 2009 monsoon (panel E). Baseline statistics are drawn from the initial baseline survey whenever possible. Since logistical constraints limited the length of the baseline survey, a subset of variables were collected using recall questions in the first follow-up survey conducted just after the 2009 monsoon. Respondents in the follow-up survey were asked to report fixed characteristics (e.g., years of schooling) and provide recall data on the value of land and other assets as of June 2009.

Panel A presents demographic data. The average household has 5.15 members with a 50-year old household head that is usually (91%) male. Panel B reports measures of education for the household head. On average, heads have obtained 3.75 years of schooling, with slightly more than half (54%) self-reporting being "unschooled." Literacy is low, with only 43 percent and 40 percent of heads self-reporting being able to read and write, respectively. These statistics are similar to those reported in our previous work (e.g., see statistics in Cole et al. (2013), which are based on a 2006 survey instrument). Online Appendix Table OA1 reports additional summary statistics for savings, credit, and assets.

Given that insurance provision was randomized, we should not observe systematic differences in baseline characteristics between the treatment and control groups. We confirm this in Online Appendix Table OA2, for demographic characteristics, the household head's education, knowledge, trust, expectations, financial assets and credit, livestock and other assets including land, and agricultural investments in the prior monsoon. Validating

Table 1
Summary statistics

Variable	Mean	SD	p10	p50	p90
A. Demographic characteristics					
Household size	5.15	2.05	3	5	8
Age of household head (years)	49.6	12.4	35	50	65
Gender of household head (1 = "male")	0.91	0.28	1	1	1
B. Education of household head					
Highest level of schooling completed by head (years)	3.75	4.76	0	0	11
Household head is unschooled (1 = "yes")	0.54	0.50	0	1	1
Household head has 1 to 5 years of schooling (1 = "yes")	0.15	0.35	0	0	1
Household head has more than 6 years of schooling (1 = "yes")	0.31	0.46	0	0	1
Household head able to read (1 = "yes")	0.43	0.50	0	0	1
Household head able to write (1 = "yes")	0.40	0.49	0	0	1
Raven's test of analytic intelligence, household head (0-3)	1.58	0.97	0	2	3
C. Knowledge, trust, and expectations of household head					
Insurance knowledge index (0-5)	1.73	2.12	0	0	5
Head has heard of rainfall insurance (1 = "yes")	0.42	0.49	0	0	1
Trust in BASIX (1 if trust > 4/10, 0 otherwise)	0.40	0.49	0	0	1
St. dev. of expected cash crop yield (kg/acre)	46.2	38.1	14.1	35.4	88.3
D. Credit and assets					
Bank credit (1 = "yes")	0.71	0.46	0	1	1
Any Credit (1 = "yes")	0.91	0.29	1	1	1
Total area of agricultural land (acres)	5.37	5.47	1.75	4	10
Wealth index (principal component)	0.00	1.70	-2.1	0.03	2.07
E. Land use and agricultural investments in 2009 monsoon					
All crops					
Positive investment/Any agricultural input used? (1 = "yes")	0.97	0.17	1	1	1
Total cultivated land (acres)	3.98	3.69	1	3	8
In which Kartis did farmer plant?	15.73	2.83	13	16	19
Market value of agricultural inputs used (Rs.)	22934	22169	5500	16550	46000
Cash crops					
Positive invesment/Any agricultural input used? (1 = "yes")	0.47	0.50	0	0	1
Total cultivated land (acres)	1.80	2.93	0	0	5
In which Kartis did farmer plant?	15.25	2.41	13	15	18
Did farmer replant crop in 2009 monsoon? (1 = "yes")	0.05	0.23	0	0	0
Did farmer abandon crop in 2009 monsoon? (1 = "yes")	0.15	0.36	0	0	1
Market value of agricultural inputs used (Rs.)	6195	12174	0	0	17700
Share of total cultivated land devoted to cash crops	0.39	0.45	0	0	1
Share of market value of ag. inputs devoted to cash crops	0.36	0.43	0	0	1

Summary statistics for the sample of 1,479 individuals that participated in both the baseline and follow-up surveys. Sections A through D report baseline characteristics at the start of the monsoon for the entire sample. Section E reports ex post investment variables for the control group (the sample of 736 individuals that did not receive the insurance treatment). See the Appendix for variable definitions.

the randomization, we find a statistically significant difference between the two groups at the ten percent level or lower for only one out of 59 variables (the use of non-traditional savings). An F-test of the null hypothesis that all average characteristics are the same for the treatment and control groups cannot be rejected (p-value = 0.67).

Table 2
Policy Details

Reference station	Start date	End date	Strike (mm)	Exit (mm)	Per mm (Rs.)	Maximum payout	Realized payout per policy (Rs.)	Number of treatment farmers
Atmakur	June 12	July 16	45	5	10	1,000	0	38
Narayanpet	July 1	August 4	50	5	10	1,000	341.5	170
Mahbubnagar	June 6	July 10	70	10	10	1,000	0	112
Hindupur	July 1	August 4	25	0	10	1,000	1,000	242
Anantapur	July 1	August 4	30	5	10	1,000	210	175

This table reports insurance policy details and payouts for the study year. The “Strike” level is the rainfall threshold below which the policy begins to pay; the policy pays the amount indicated in “Per mm” for each mm of shortfall below this threshold. The “Exit” level is the rainfall threshold below which the policies pays the “Maximum Payout.” The “Realized Payout per policy” reports the payout received by insured farmers in 2009. Each farmer in the treatment group received ten insurance policies. The Mahbubnagar and Anantapur stations are owned and operated by the Indian Meteorological Department. The other three weather stations were installed in 2005 by INGEN, a private company, for the purposes of the rainfall insurance program.

Panel E presents control group summary statistics for agricultural investments during the 2009 monsoon, drawn from the first follow-up survey. We collected data on area of land sown with cash crops (castor or groundnut) and all crops, the timing of planting, and amounts spent and used for different agricultural inputs. For a subset of inputs, we also measured input usage for cash crops, in addition to total usage. A very high share (97%) of farmers planted some crop, and roughly half (47%) planted cash crops. Fewer farmers planted cash crops in 2009 than 2008, reflecting the poor 2009 monsoon. Also reflecting the poor monsoon, 15% of farmers abandoned their crop during the 2009 monsoon season. Online Appendix Table OA3 presents disaggregated statistics for usage and spending on individual inputs, including seeds, fertilizer, manure, pesticide, irrigation and hired labor.

Table 2 summarizes contract details and realized payouts for the five insurance policies (recall that farmers received policies linked to different rainfall stations, depending on their village location). Three of the five policies realized a positive payout, and the 242 treated farmers with insurance indexed to Hindupur station rainfall received the maximum payout of Rs. 1,000 per policy (Rs. 10,000 in total). In Section 3, we use variation in payouts across rainfall stations to distinguish between ex ante and ex post effects of insurance provision. In Section OA2 of the Online Appendix, this variation in payouts is used to help identify how insurance payouts were ultimately used by farmers.

3. Estimation results

3.1 Insurance treatment effects

Table 3 presents the estimated average treatment effects of insurance provision on farmers’ agricultural decisions during the 2009 monsoon season. We analyze five outcome variables: (i) a dummy equal to one if any agricultural inputs were used during the monsoon, (ii) the log of the acres of land sown, (iii) the log of the market value of agricultural inputs used, and two shares, (iv) the share

Table 3
Effects of insurance on agricultural investments

	Estimator	Mean of dep. variable for control group	Percent of control group = 0	Household covariates included? No	Household covariates included? Yes
Dependent variable:	(1)	(2)	(3)	(4)	(5)
A. Investments in all crops					
Positive investment/Any ag. inputs used (1 = Yes)	Probit	0.97	3	0.012	0.009
				(0.011)	(0.008)
ln(1+total cultivated land, acres)	Tobit	1.39	7	0.028	0.039
				(0.034)	(0.031)
ln(1+market value of ag. inputs used, Rs.)	Tobit	9.45	3	0.082	0.110
				(0.087)	(0.083)
B. Investments in cash crops					
Positive investment/Any ag. inputs used (1 = Yes)	Probit	0.47	53	0.060**	0.064**
				(0.029)	(0.030)
ln(1+total cultivated land, acres)	Tobit	0.66	54	0.086**	0.093***
				(0.037)	(0.036)
ln(1+market value of ag. inputs used, Rs.)	Tobit	4.24	53	0.451**	0.485**
				(0.218)	(0.216)
Cash crop shares					
Share of total cultivated land planted with cash crops	Tobit	0.39	52	0.047**	0.048**
				(0.021)	(0.021)
Share of market value of ag. inputs devoted to cash crops	Tobit	0.37	51	0.034*	0.035*
				(0.019)	(0.019)

This table reports the marginal effect of the insurance treatment dummy on various measures of monsoon agricultural investments; each row presents a different dependent variable. The first three dependent variables relate to investments in all crops. Dependent variables in the next three regressions relate to investments in cash crops only. The final two specifications consider the share of total agricultural inputs used for growing cash crops. Two versions of each model are presented, one without additional household covariates (Column 4) and one with (Column 5). These household covariates are Age of head, Education of head, and the Wealth index. Cash crops are defined as castor in Mahbubnagar and groundnut in Anantapur. Robust standard errors. All specifications include village dummies and a dummy for whether the household received the fertilizer discount. Sample includes the 1,479 farmers that completed both the baseline and follow-up surveys. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

of total cultivated land and (v) the share of market value of agricultural inputs devoted to cash crops. Panel A (B) reports the estimates for all (cash) crops, respectively.

Each outcome variable is regressed on a dummy for whether the farmer received the insurance treatment (the key variable of interest), a set of village dummies, a dummy for each fertilizer treatment, and, in some regressions, a set of household characteristics[12]. Column 2 reports the mean of the dependent variable for the control group, while Column 3 reports the percentage of observations equal to zero.

To conserve space, only results for the key coefficient on the insurance treatment dummy are reported. Coefficients are presented in columns 4 and

[12] We use probit for binary outcomes and tobit for censored outcomes. As a robustness check, we also estimated Table 3 using a linear probability model (see Online Appendix Table OA4). Results are similar. Note that Fernández-Val (2009) shows that estimates of marginal effects based on a probit are either unbiased or exhibit negligible bias, even though probit and tobit estimators generally produce biased estimates of the structural model parameters in the presence of fixed effects.

5, reported as marginal effects. In Panel A, we find a positive, although not statistically significant, effect of the insurance treatment on the quantity of inputs used or the area of land cultivated. However, when the analysis is restricted to castor and groundnut investments in Panel B, the treatment effects become much larger and are also statistically significant at the 5% level or lower in each specification. Quantitatively, assignment to the insurance treatment group increases the probability of planting cash crops by 6 percentage points (or 12 percent). We estimate an increase in ln(1+land planted for cash crops) of 0.086 (Tobit marginal effect).[13] As shown in the "cash crop shares" results in panel B, assignment to the insurance treatment group increases the share of total cultivated land devoted to cash crops by 4.7 percentage points and the share of inputs (measured by market value) by 3.4 percentage points.

Column 5 of Table 3 reports results controlling for three household characteristics: age, years of education, and wealth. Adding these controls has little effect on the estimates, consistent with the random assignment of farmers to the treatment and control groups.

To summarize, we find significant increases in the quantity of cash crop investments by farmers randomly assigned to receive rainfall insurance policies and the share of total investments directed to cash crops. The effects on total agricultural investments, while positive, are not statistically significant. This latter result could be consistent with the presence of fixed short-run production factors (e.g. a given amount of arable land owned by the farmer, which cannot be easily adjusted in the short run) or the presence of financial constraints.[14] It may also simply reflect our limited statistical power.

The estimates in Table 3 represent local average treatment effects. Figure 3 instead plots the cumulative distribution function of investment in cash crops by insurance treatment status. This plot suggests that the effect of the insurance treatment is quite non-linear. Insurance causes a sizeable number of farmers to switch on the extensive margin from not growing cash crops into growing cash crops, consistent with the probit regression estimates. But for farmers in the top part of the distribution of cash crop investments, insurance provision has little or no effect on cash crop inputs used. In other words, the provision of insurance appears to primarily affect the extensive margin of investment decisions.

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[13] Online Appendix Table OA5 also reports regression results for cash crop usage split up by individual agricultural inputs type (hybrid seeds, improved seeds, fertilizer, etc.). The disaggregated treatment effects are positive in each regression, although because of the much lower power, not usually statistically significantly different from zero.

[14] Table OA6 of the Online Appendix analyzes the effect of the insurance treatments on various measures of the take-up of credit during the 2009 monsoon, when agricultural investment decisions were made. We find that treated farmers are no more likely to take up credit (of any form) than farmers in the control group, suggesting that being insured did not relax credit constraints.

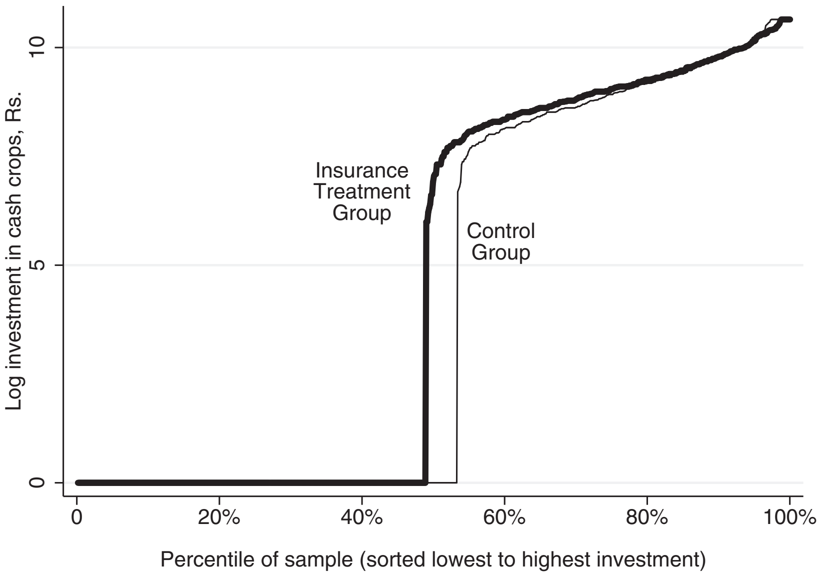

Figure 3
Cumulative density, log investment in cash crops
The y-axis plots the natural log of 1 + the amount invested in cash crops (in Rs.) for the treatment and control groups. Farmers in each group are sorted in increasing order of cash crop investments.

Figure 3 also reveals that there is a discrete jump in the level of cash crop investment once the farmer decides to invest a positive amount. This points to the presence of scale economies; farmers do not sow a given crop below a minimum scale. Around this decision threshold, the provision of insurance against income risk makes farmers more willing to invest a positive amount in castor and/or groundnut. According to our data, the minimum area cultivated under cash crops is 0.5 acres, accounting for 10 percent of average landholdings. For farmers planting cash crops, the median area under cash crops cultivation is 3 acres (70 percent of landholdings).

3.2 Heterogeneous treatment effects

In Table 4, we test for heterogeneity in the insurance treatment effect along several dimensions, including household wealth, age, education, knowledge, trust and payouts. We estimate regressions of the form:

outcome $= f(a+b.$ insurance $+c.$ characteristic $+d.$ insurance x characteristic + …+ e),

where “insurance” is a dummy equal to one if the farmer was assigned to the insurance treatment group, and “characteristic” is the source of heterogeneity of

Table 4
Heterogeneous effects of insurance treatment

Dependent variable: Positive investment in cash crops (1 = Yes)

	Baseline model [as Table 3]	Single interactions of treatment with:						Multivariate
		Wealth	Age	Education	Knowledge	Trust	Payouts	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Insurance treatment dummy	0.060**	0.062**	0.014	−0.004	0.067*	0.064*	0.033	−0.196
	(0.029)	(0.029)	(0.123)	(0.037)	(0.039)	(0.038)	(0.045)	(0.143)
Interaction effects:								
treat x Wealth index		−0.012						−0.022
		(0.018)						(0.020)
treat x Age of head			0.001					0.004
			(0.002)					(0.003)
treat x Education of head (years)				0.018***				0.024***
				(0.006)				(0.007)
treat x Insurance knowledge index (0-5)					0.022			0.013
					(0.034)			(0.036)
treat x Head has heard of rainfall insurance					−0.104			−0.088
					(0.143)			(0.151)
treat x Trust BASIX (1 = yes)						−0.008		−0.001
						(0.061)		(0.068)
treat x Payout (1,000 Rs.)							0.059	0.033
							(0.073)	(0.078)

(continued)

Table 4
Continued

Dependent variable: Positive investment in cash crops (1 = Yes)

	Baseline model [as Table 3]	Single interactions of treatment with:						
		Wealth	Age	Education	Knowledge	Trust	Payouts	Multivariate
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Uninteracted household characteristics:								
Wealth index		0.041***						0.048***
		(0.013)						(0.014)
Age of head			−0.002					−0.004**
			(0.002)					(0.002)
Education of head (years)				−0.005				−0.013**
				(0.005)				(0.005)
Insurance knowledge index					−0.065**			−0.063**
					(0.026)			(0.027)
Head has heard of rainfall insurance (1 = yes)					0.292***			0.286**
					(0.110)			(0.112)
Trust BASIX (1 = yes)						0.022		−0.001
						(0.044)		(0.048)
Payout (1,000 Rs.)							na	na

This table reports the marginal effects on cash crop investments of the insurance treatment dummy, as well as interactions between the treatment dummy and various household characteristics. The dependent variable is equal to one if the farmer invested resources in planting cash crops. Since the "knowledge of insurance" questions were only asked of farmers who were aware of insurance, the specification including the knowledge index also includes a dummy for whether the farmer had heard of insurance. No direct effect of insurance contract payout on investment reported since payout only varies by village, and is absorbed by village dummies. Cash crops are defined as castor in Mahbubnagar and groundnut in Anantapur. Probit estimator. Robust standard errors. All specifications include village dummies and a dummy for whether the household received the fertilizer discount. Sample includes the 1,479 farmers that completed both the baseline and follow-up surveys. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

interest (e.g. wealth, age, education etc.). Our primary interest is the coefficient d on the interaction term.

Table 4 presents results using the dummy variable indicating whether the farmer plants cash crops as the outcome variable. Column 1 of Table 4 reproduces the estimate from Table 3. Columns 2 – 7 include the six different characteristics, one at a time, and their interaction with the insurance treatment dummy. Column 8 includes all the characteristics and interactions together. The top part of the table reports the estimated interaction effects, while the uninteracted effects are reported below. As before, coefficients are reported as marginal effects.

In Column 2, we study how the insurance treatment effect varies with wealth, measured by an index constructed as the first principal component of asset holdings (see the Appendix for details of variable construction for this index and selected other variables used in this study). It is unclear theoretically what effect to expect. On one hand, wealthy farmers may already have informal insurance arrangements or the ability to smooth temporary income shocks (e.g., because they have sufficient liquid assets or access to credit), reducing their need for rainfall insurance, as in Mobarak and Rosenzweig (2013), or may be locally less risk averse, if utility exhibits decreasing absolute risk aversion. On the other hand, wealthy farmers may find it easier to adjust agricultural practices in response to a shift in the risk-return frontier due to insurance (e.g., because they are less financially constrained). Empirically, we find that the treatment effect is decreasing in wealth, but the relationship is not statistically significant. The direct effect of wealth is, however, positive and statistically significant at the 1 percent level; in other words, as expected, wealthy farmers are much more likely to invest in cash crops. Column 3 considers heterogeneity by age of the household head. The interaction term is economically small and not statistically significant.

Column 4 considers heterogeneity in treatment effects by educational attainment, measured by years of education of the household head. Strikingly, we find positive, economically important, statistically significant interaction effects, implying that the treatment effect of insurance provision is concentrated amongst educated farmers. Quantitatively, an additional year of education increases the effect of the insurance treatment on the probability of planting cash crops by 1.8 percentage points, significant at the 1 percent level. Furthermore, the treatment effect is not statistically or economically different from zero for farmers without formal education. We further investigate the role of education in shaping farmers' response to insurance in Section 3.C below.

Column 5 examines whether the treatment effect varies with the farmer's understanding of how insurance works, measured by the number of correct answers to questions on the circumstances under which a payout would be received, and awareness of the product, while Column 6 tests whether the treatment effect varies with the farmer's trust in Basix, the insurance vendor.

Interestingly, unlike education, neither the knowledge or trust interaction terms are statistically significant.

Column 7 uses ex post realized payouts as the interaction variable. This provides a test of whether farmers' investment responses might reflect their expectation of receiving a high payout in the future (e.g. because of early information that the monsoon is likely to be poor). If true, this would change the interpretation of our results, since it would imply that our treatment effect reflects factors other than just the hedging benefits of insurance. This interaction variable is quantitatively small and not statistically significant, implying that the investment response is not driven by this anticipation effect.

Finally, Column 8 includes all the interaction variables jointly rather than one at a time. Consistent with the results from columns 2 – 7, only the heterogeneous treatment effect by educational attainment is statistically significant. The coefficient on years of education x treatment increases slightly compared to Column 4, from 0.018 to 0.024, and remains statistically significant at the 1 percent level.

We repeat this analysis using two other dependent variables, the log area of land planted with cash crops and the log value of the investment in cash crops. To conserve space, results are presented in tables OA7 and OA8 of the Online Appendix. Results are very similar to Table 4. The treatment effect of insurance is economically much larger for educated farmers, statistically significant at the 1 percent level. None of the other interaction variables are statistically significant

We also analyze heterogeneity in the insurance treatment effects by other characteristics measured at or before baseline (results reported in Table OA9 of the Online Appendix), including current or recent indebtedness (as a measure of financial slack); wealth and wealth squared (to measure potential nonlinear or threshold heterogeneous treatment effects by wealth); landholdings (as an alternative measure of wealth); a threshold level of land (to test whether farmers with small plots may be less able to switch to cash crops because of minimum scale effects); two measures of experience with insurance: a dummy for whether the farmer previously purchased rainfall insurance and an instrumented dummy for whether the farmer purchased insurance in 2006 using the randomized treatments from Cole et al. (2013) as instruments for purchase; and a measure of the subjective variance of expected agricultural yields as self-reported by the farmer. None of these interaction effects is statistically significant, either when included one at a time or all together.

Summing up, the main source of heterogeneity that we are able to identify given the power of our statistical tests is the farmer's level of educational attainment. Consistent with this result, Karlan et al. (2014) finds in a different setting that insurance has larger effects on investment when the household head can read. Related, some previous research finds evidence that education is positively correlated with take-up of rainfall index insurance or an insured loan (Cole et al. 2013; Giné and Yang 2009).[15] We note that while the insurance treatment is randomly assigned, education, of course, is not. Thus, our results could reflect omitted variables that are correlated with educational attainment but not captured by age, wealth, trust, or the other variables included in Table 4 or Table OA9. Although we cannot fully rule out the presence of such omitted variables, we do view the education result as quite striking, given its significance and robustness to which other interaction terms are included in the specification. We turn to a more detailed analysis below.

3.3 Further Analysis of Education Heterogeneous Treatment Effects

Table 5 presents further analysis to investigate *why* education is so important in shaping farmers' responses to the insurance treatment. We test whether the heterogeneous treatment effects (HTE) by education are limited to particular subsets of the sample (e.g., farmers with more land or with bank debt), investigate the effects of adding interactions between the insurance treatment and other measures of cognitive skills, and study the functional form of the education HTE.

We regress a dummy equal to one if the farmer planted cash crops on a set of education variables and interaction terms of interest, controlling for all the farmer characteristics and interaction terms from the multivariate regression in Column 8 of Table 4 (e.g., wealth, treatment x wealth, age, treatment x age, and so on). We do this to minimize concerns about omitted variable biases. Our main results are robust to whether or not these additional controls are included.

Column 1 of Table 5 reproduces Column 8 of Table 4 for ease of reference. Column 2 examines functional form: it adds to the specification from Column 1 two "step function" dummies measuring categories of educational attainment (1-5 years of education and 6+ years of education) and their interactions with the insurance treatment. The linear education interaction variable (years of education x treatment) remains statistically significant, while the two additional interaction terms are not significant, either individually or jointly. In other words, we cannot reject the null that the effect of insurance on cash crop investments increases linearly with years of education. While our statistical power is limited, this result speaks against the hypothesis that our effect only appears beyond a minimum threshold level of education, especially because the point estimate on the 6+ years dummy is negative.

Columns 3 and 4 include interactions between the insurance treatment and two other measures of cognitive skills: a dummy for whether the farmer self-reports that they can read and the farmer's score in a short three-question Raven test, a well-known nonverbal test of analytic intelligence based on pictograms (Raven 2000; Pind, Gunnarsdottir and Johannesson 2003; Carpenter, Just and Shell 1990). The goal of this analysis is to test whether our result is driven

[15] An insured loan in Giné and Yang (2009) is a debt contract bundled with an insurance policy with a maximum payout equal to the principal and interest to be repaid.

Table 5
Education and the effects of insurance on agricultural investments

Dependent variable: Positive investment in cash crops (1 = yes)

	Education interaction variable(s):						
					Education interacted with:		
	Education (years) [as Tab 4 Col 8]	Additional education dummies	Literacy + years of education	Raven's score + years of education	Land-holdings	Bank credit usage	St. dev. of expected ag yield
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Insurance treatment dummy	−0.196	−0.184	−0.197	−0.210	−0.231	−0.170	−0.122
	(0.143)	(0.146)	(0.144)	(0.152)	(0.151)	(0.155)	(0.150)
Interaction effects:							
treat x Education of head (years)	0.024***	0.048**	0.022*	0.024***			
	(0.007)	(0.020)	(0.013)	(0.007)			
treat x Education = 1–5 years		−0.075					
		(0.120)					
treat x Education = 6 + years		−0.258					
		(0.177)					
treat x Head can read			0.013				
			(0.120)				
treat x Raven's test score				0.005			
				(0.032)			
treat x Education x landholdings > median					0.029***		
					(0.009)		
treat x Education x landholdings < median					0.014		
					(0.011)		
treat x Education x bank credit						0.027***	
						(0.008)	
treat x Education x No bank credit						0.014	
						(0.013)	
treat x Education x SD of exp yield > median							0.044***
							(0.010)
treat x Education x SD of exp yield < median							0.007
							(0.009)

(*Continued*)

Table 5
Continued

	Education interaction variable(s):						
					Education interacted with:		
	Education (years) [as Tab 4 Col 8]	Additional education dummies	Literacy + years of education	Raven's score + years of education	Land-holdings	Bank credit usage	St. dev. of expected ag yield
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Uninteracted education measures							
Education of head (years)	−0.013**	−0.042***	−0.019**	−0.013**			
	(0.005)	(0.015)	(0.009)	(0.005)			
Education = 1–5 years		0.144*					
		(0.086)					
Education = 6 + years		0.314**					
		(0.139)					
Head can read			0.071				
			(0.084)				
Raven's Test score				−0.033			
				(0.024)			
Education x landholdings >median					−0.023***		
					(0.007)		
Education x landholdings <median					0.001		
					(0.007)		
Education x bank credit						−0.016***	
						(0.006)	
Education x no bank credit						−0.004	
						(0.009)	
Education x SD of exp yields >median							−0.024***
							(0.007)
Education x SD of exp yields <median							−0.004
							(0.006)
Landholdings dummies	no	no	no	no	yes	no	no
Bank credit dummies	no	no	no	no	no	yes	no
SD of exp yield dummies	no	no	no	no	no	no	yes
Other covars. from Table 4?	yes	yes	yes	yes	yes	yes	yes

(*Continued*)

Table 5
Continued

	Education interaction variable(s):				Education interacted with:		
	Education (years) [as Tab 4 Col 8]	Additional education dummies	Literacy + years of education	Raven's score + years of education	Land-holdings	Bank credit usage	St. dev. of expected ag yield
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Hypothesis tests on interaction variables							
Joint significance: 1–5 and 6 + yrs education		0.387					
Joint significance: literacy and education			0.003				
Joint significance: Raven's and education				0.003			
Equality: high vs low landholding					0.272		
Equality: Bank credit vs no credit						0.381	
Equality: High SD vs Low SD of exp yields							0.004

This table reports the marginal effects on cash crop investments of the insurance treatment dummy and various interactions between the insurance treatment and measures of education and cognition. All specifications include other covariates from Table 4 (wealth, age, knowledge of insurance/heard of insurance, trust, and payouts) and their interactions with the treatment dummy. "Landholdings dummies" refers to dummy for landholdings > median and the interaction term landholdings > median x treatment. "Bank credit dummies" and "SD of exp yield dummies" are similarly defined. Cash crops are defined as castor in Mahbubnagar and groundnut in Anantapur. Probit estimator. Robust standard errors. All specifications include village dummies and a dummy for whether the household received the fertilizer discount. Sample includes the 1,479 farmers that completed both the baseline and follow-up surveys. *, **, and *** denote significance at the 10%, 5% and 1% level, respectively.

by a particular facet of education, either literacy or analytic reasoning. In both cases, the additional interaction variable is positive, although small and not statistically significant, while the coefficient on education x treatment barely changes in size. This suggests that the education HTE is not driven narrowly by either of these dimensions of cognitive skill.

Columns 5, 6 and 7 include triple-interaction terms to study whether education is a necessary but not sufficient condition for insurance provision to induce changes in production behavior. We split the sample in turn by: (i) landholdings (above vs below median), (ii) usage of bank credit at baseline (any vs none), and (iii) farmers' self-reported estimates of the standard deviation of agricultural yields, a measure of how risky the farmer perceives the environment to be (above vs below median).[16] We then interact the education interaction term with this additional variable; e.g., Column 5 includes treatment x education x landholdings >median and treatment x education x landholdings <median. Specifications also include all the relevant non-interacted variables and single and double interactions.

Looking at columns 5 and 6, the point estimates on the "above median landholdings" and "any bank credit usage" triple interaction variables are positive and significant, respectively, while the corresponding coefficients for the "below median land" and "no bank credit" groups are about half as large and not statistically significant. However, our estimates are not precise enough in either case to reject the null that the coefficients on the two triple interaction terms are equal, as reported at the bottom of Table 5. In other words, the heterogeneity in treatment effects by education is more pronounced for farmers with more land or access to credit but not statistically significantly so.

However, in Column 7, we find evidence that the insurance treatment effects are concentrated in the subset of farmers that are both educated *and* believe that agricultural yields are highly volatile. For such farmers, an additional year of education increases the probability of planting cash crops by 4.4%, statistically significant at any conventional level ($p < 0.001$). This is more than five times the coefficient for the "low variance of yields" group of 0.7%. Unlike columns 5 and 6, we can reject the null that the treatment effect is the same for the two groups; the difference between these two coefficients is statistically significant at the 1 percent level, as shown at the bottom of Table 5. Although we do not want to over-interpret this finding, it is suggestive that educated farmers may be better able to "think through" the relationship between insurance and riskiness of agricultural investments and the implications for optimal risk-taking.

To conserve space, Table 5 focuses only on one dependent variable: a dummy for whether the farmer made any cash crop investments. Tables OA10 and OA11 of the Online Appendix repeat the analysis using the two other dependent

[16] We compute this variable by eliciting from each farmer a histogram of the distribution of agricultural yields. Specifically, each farmer was asked to arrange a set of 10 stones across different ranges for agricultural yields to indicate the relative likelihood of different outcomes. See the Appendix for more details.

variables from Table 3: the area of land planted with cash crops and the value of the investment in cash crops. Results are similar to those presented above.

Taken together, our results imply that education more broadly, rather than just literacy or analytic intelligence or even prior knowledge about rainfall insurance, is important for determining whether farmers change production behavior when insured. Our data do not allow us to pin down the exact mechanism within education. We speculate that education may help teach farmers to solve problems and evaluate unfamiliar situations and that a well-educated farmer, even if unfamiliar with a specific financial product, will be better able to learn about the product as needed once they receive it and to logically reason how access to the product should influence other decisions. Our evidence that the insurance treatment effect is concentrated among farmers who are both educated *and* view yields as highly volatile suggests that education helps farmers think through the complex relationship between production risk, insurance, and agricultural decisions.

It would, of course, be interesting to conduct similar analysis in other settings, both to test the external validity of our findings and to further "unpack" the mechanisms underlying the education results presented here. Furthermore, we find that subjective perceptions of agricultural risk affect educated farmers' responses to insurance provision; since these perceptions may reflect a combination of objective information and individual beliefs, it would be informative to test whether similar results hold using objective measures of production risk (e.g., exploiting differences in topography or weather volatility across regions). If results are indeed similar, it would strengthen the case that insurance provision promotes risk-taking in environments in which underlying income risks are extreme. More generally, our finding that education affects farmers' responses to insurance provision has potentially interesting implications for the distributional effects of financial innovation. Specifically, new financial instruments that change the tradeoffs between risk and return may increase income inequality by educational attainment, at least during a transition period, if educated households are more likely to change behavior in response to the change in the feasible set of risk-return outcomes.[17]

3.4 Timing

Figure 4 presents evidence on how the insurance treatment affects the *timing* of cash crop investments. This figure is constructed by estimating regressions similar to Table 3, tracing out how the insurance treatment affects the probability of planting cash crops by different points in the monsoon season. Specifically, each point on the graph represents the marginal effect from a probit regression, where the dependent variable is equal to 1 if the farmer had planted cash crops

[17] See Townsend and Ueda (2006) for a model-based quantitative evaluation of the relationship between economic growth, financial deepening, and inequality in an emerging market context (the Thai economy between 1976–1996).

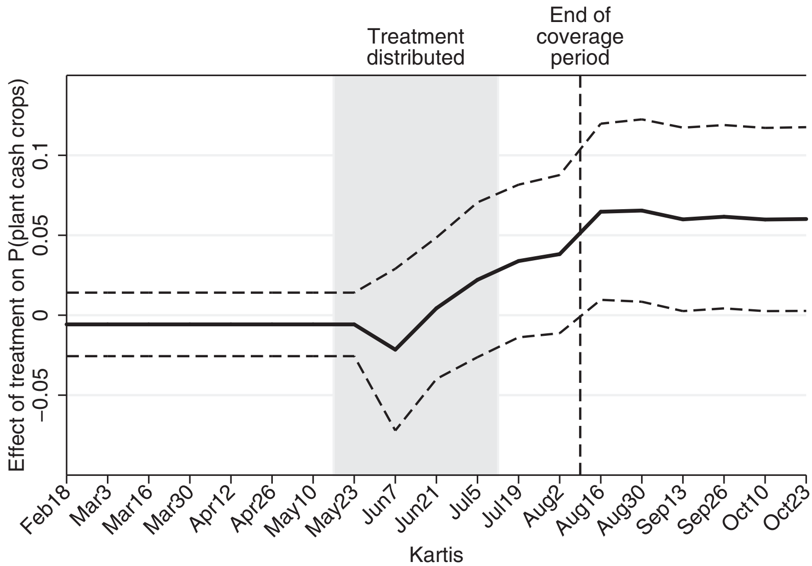

Figure 4
Effect of insurance treatment status on timing of cash crop investments
The x-axis of the figure plots the passage of time in 2009, measured in terms of "kartis" (a kartis is a variable period of time approximately two weeks in length). The label below each tick mark reports the first date of the kartis. The y-axis plots the effect of insurance treatment status on the probability of having planted cash crops by the kartis in question. The shaded region indicates the period during which the insurance policies were distributed to treated farmers. The dashed vertical line indicates the end of the coverage period for any of the insurance policies. The solid line displays the point estimate of the insurance treatment effect; the dashed lines above and below the solid line represent a 95% confidence interval.

by date t. The explanatory variables are the insurance treatment dummy and the other controls from Column 4 of Table 3. Vertical lines indicate the period in which insurance policies were distributed and the end of the time period covered by any of the five insurance policies.

As expected, the insurance treatment effect is close to zero at the point when the insurance policies are randomly allocated to farmers. The cumulative treatment effect by date then rises sharply, becoming statistically significant by the end of the insurance coverage period. It subsequently flattens out and converges to the point estimate from the average treatment effect regression in Table 3.

To summarize, this analysis shows that the effects of the insurance treatment on behavior occur during the planting season, prior to the end of the insurance coverage period and several months before the insurance payout is received. This suggests that insurance induced farmers to take riskier production decisions during the planting season in the knowledge that they would be partially hedged in the event of a poor monsoon. An alternative hypothesis is that our results are responses to the ex post receipt of insurance payouts or the anticipation of future payouts. This hypothesis is not consistent with the

Table 6
Self-reported effects of rainfall insurance on agricultural investments

Effect of rainfall insurance on:			
Amount used of	More	No change	Less
Fertilizer	50%	36%	14%
Seeds	41%	43%	16%
Pesticides	32%	41%	27%
Bullock labor	23%	48%	29%
Hired labor	35%	42%	23%
Funds borrowed to finance agricultural inputs	26%	52%	22%
Timing of initial planting			
Earlier	26%		
No change	69%		
Later	5%		
Decision of whether to abandon crops			
Against	26%		
No change	67%		
Towards	7%		

This table tabulates the self-reported effects of rainfall insurance on investment decisions, as reported by 743 farmers in the treatment group. This information was collected during the first follow-up survey, conducted in late 2009.

timing of the behavioral response in Figure 4, however; also speaking against this explanation, our analysis in Table 4 finds no correlation between treatment effects of insurance and realized ex post payouts. In other words, the insurance treatment effects we observe appear to reflect the relaxation of a risk constraint, rather than a wealth effect or relaxation of credit constraints.

3.5 Qualitative self-reported changes in behavior

Complementing this statistical analysis, the follow-up survey conducted after the 2009 monsoon simply asked farmers in the insurance treatment group to self-report whether and how the provision of insurance affected their investment behavior. We asked farmers whether the knowledge of being insured led to an increase, decrease, or no change in the amount of fertilizer, seeds, and other inputs they used, and whether it influenced decisions about planting, replanting and/or abandoning crops. Responses are summarized in Table 6.

Between 36-52% of farmers report not changing their behavior, depending on the question. Among the remainder, a significantly larger fraction reported increasing agricultural input usage as opposed to reducing it. This was true for five of six inputs; e.g., 50% reported using more fertilizer, while only 14% reported using less. The exception was bullock labor (23% more, 29% less). Farmers also report that it influenced them towards planting earlier (26%, compared to 5% who report being influenced to plant later) and against abandoning crops. We view this evidence as suggestive at best, given the well-known biases associated with responses to subjective survey questions (Bertrand and Mullainathan 2001) and the difficulty farmers may have in introspectively assessing what their behavior would have been in the counterfactual situation in which they did not have insurance. Bearing these caveats in mind, the direction of farmers' responses seem consistent with our econometric evidence that insurance induces investment in risky agricultural activities.

3.6 Additional robustness checks

Three additional sets of robustness checks are reported in the Online Appendix (see tables OA12, OA13 and OA4). First, to test the sensitivity of our results to the transformation ln(1+variable) used for two of the dependent variables in Table 3, we re-estimate these results using alternative transformations of the form ln(x+variable), where x is set to 10, 0.1, 0.01 instead of 1, as well as using an inverse hyperbolic sine transformation instead of a log transformation. Our results on cash crop investments are robust to these alternative transformations. For a few of the alternative log transformations, insurance also has a marginally statistically significant positive effect on total investment; these effects are positive, although not statistically significant, in Table 3.

Second, to test for the influence of outliers, we re-estimate our main results from Table 3 after winsorizing the top and bottom 2% of all continuous variables. Results are almost unchanged, suggesting that the logarithmic and share transformations already do a good job of limiting the influence of extreme observations.

Third, as mentioned earlier, we find similar estimated marginal effects of the insurance treatment if we estimate the specifications from Table 3 using a linear probability model, rather than tobit and probit estimators.

3.7 Impact of Insurance Payouts

Unexpectedly, southern India experienced a severe drought during the monsoon season of the year of our experiments. Reflecting the low realized rainfall during the rainfall insurance coverage period, many insured farmers received significant cash payouts ranging from Rs. 2100 (ca. $42) to Rs. 10,000 (ca. $200), as indicated in Table 2. Section OA2 of the Online Appendix presents evidence on what farmers did with these payouts, based on data from a second follow-up survey conducted in mid-2010. We briefly summarize this evidence below.[18]

We first tabulate farmers' self-reported accounting of how payouts were used. Farmers report that roughly half of the funds were used for consumption or agricultural investments, with the rest saved, used to retire debt, or given

18 This analysis is omitted from the main text in part because our statistical power is low; in addition, this evidence is less novel than our analysis of the ex ante effects of insurance, as there is already a significant body of well-identified research on how households use unexpected cash windfalls (e.g., de Mel, McKenzie and Woodruff 2008).

away. Only around one-tenth of funds were given away, and such gifts were generally restricted to the farmer's family. Like our earlier evidence on self-reports, these results should be treated with caution: Karlan, Osman and Zinman (2016), for example, show in the context of micro-credit that individuals do not accurately self-report expenditures when receiving credit. Fungibility may be one source of confusion: farmers may report the proximate use of funds rather than their incremental spending relative to the counterfactual of not having received a payout. Bearing these concerns in mind, farmers' responses taken at face value suggests payouts are retained and spent by the recipient, rather than being socialized within the village.

In the more formal part our analysis, we regress a range of ex post outcomes on insurance treatment status and the size of the insurance payout as well as village dummies and other controls. Because all insured farmers in a given village received the same payout, identification comes from within-village differences between treated and untreated farmers in villages where payouts were high relative to the corresponding difference in villages where the insurance did not pay out.

We find farmers who received large payouts subsequently reported greater trust in the insurance provider, perceived less basis risk in the insurance product, and were more likely to have paid down high interest rate debt. We do not find systematic differences in subsequent investment, labor supply, or asset values, perhaps reflecting the late survey timing and low power of our estimates. We do find that farmers in the insurance treatment group who received large payouts report statistically significantly lower consumption than the control group (i.e., we can reject the joint hypothesis that treatment and treatment x payout are zero). While this result may seem counterintuitive, it may simply reflect the fact that treated farmers rationally chose to take on more risk ex ante, resulting in lower drought income that was not fully compensated by insurance payouts. It is not necessarily evidence of ex ante "mistakes."

4. Conclusions

We find that the provision of insurance against rainfall risk influences production decisions among a sample of Indian farmers. In particular, insured farmers increase agricultural investments in higher-return but rainfall-sensitive cash crops. This shift in behavior is concentrated on the extensive margin and among more-educated farmers. Investigating the timing of the change in behavior, we show that it occurs ex ante, before the resolution of uncertainty about the timing of the monsoon.

These findings, as well the results of other recent complementary research, imply that farmers are underinsured and that insurance arrangements that "fill in" missing markets have significant effects on entrepreneurial production and risk-taking. Financial innovations that help pool and diversify risk may thus play a significant role in boosting growth and real incomes in emerging market economies. Such a role relies, however, on financial deepening and further improvements to product design and delivery that mitigate "barriers" to insurance uptake, including high prices and transaction costs, basis risk, limited familiarity and trust, and financial constraints (Cole et al. 2013; Clarke 2016; Rampini and Viswanathan 2015). In some cases, public insurance provision may be warranted if barriers to individual adoption are high due to market failures.

From a broader international perspective, the availability of insurance to mitigate income risk for entrepreneurs (and would-be entrepreneurs) varies widely across countries and over time. Examples include access to health insurance, unemployment insurance, bankruptcy protection, and social security. Analyzing the effects of insurance arrangements on entrepreneurial activity and risk-taking is a promising area for future research.

Appendix

Table A1
Selected variable definitions

Variable	Descriptive information	Survey
A. Demographic characteristics		
Age of household head	Age of the household head, in years.	2009 Follow-Up
B. Education of household head		
Education of household head	The household head's highest level of schooling completed, measured in years. 5 is equivalent to primary school completion, 7 is secondary school completion, 12 is high school completion, 13-16 correspond to Diploma/vocational course, Bachelor degree (3 years), Professional Bachelors degree (4 years), and Masters degree, respectively.	2009 Follow-Up
Literacy (farmer can read)	Dummy variable indicating that household head self-reports that they are able to read and understand a newspaper.	2009 Follow-Up
Raven's test score	Score (0-3) based on the number of correct responses to three analytic intelligence test questions. In each question, a patterned picture with a piece missing is displayed, and respondents had to select the correct piece from six choices, after being shown an example.	2010 Follow-Up
C. Knowledge, trust, and expectations of household head		
Insurance knowledge index	Individuals are asked to calculate, given a set of assumptions, whether they would get an insurance payout and how large would that payout be. Five questions are asked, with one point assigned to each 'good' response. The index is the sum of correct responses [0-5].	2009 Baseline

(*continued*)

Table A1
Continued

Variable	Descriptive information	Survey
Heard of insurance	Dummy variable equal to one if the respondent has not heard of rainfall insurance. This is used due to the skip pattern in the Insurance Knowledge Index variable (those questions are only asked if the farmer is aware of insurance).	2009 Baseline
Trust	Dummy variable equal to one if trust in the insurance vendor BASIX is greater than 4, based on the question: "on a scale of 0-10, how trustworthy do you think the BASIX organization is?", otherwise zero.	2009 Baseline
SD of expected yield (kg/acre) of cash crops without fertilizer	Each respondent reports the expected minimum and maximum yields that could be realized from one acre of land, assuming that rains are "very poor" and "very good", respectively. (This is done for castor yields in Mahbubnagar, and groundnut yields in Anantapur, and under the assumption that fertilizer is not used). The enumerator computes the midpoint M between these two yields, as well as additional midpoints halfway between the minimum and M (m1) and between M and the maximum (m2), resulting in a 5-point support. The respondent is then asked to distribute 10 beans according to the likelihood that yields will be between the minimum and m1, between m1 and M, between M and m2 and between m2 and the maximum. The standard deviation of expected yield is computed as the standard deviation of the data in this histogram.	2009 Baseline
D. Credit and assets		
Bank credit	Dummy variable equal to one if at the time of the 2009 baseline survey, the respondent either has outstanding loans from a bank, and/or has been approved for credit from a bank at least once since the end of 2008 monsoon.	2009 Baseline
Any credit	Dummy variable equal to one if, at the time of the 2009 baseline survey, the respondent either has outstanding loans from a bank, family and friends, microfinance institutions (BASIX), moneylender, or other, or equal to one if indicates that has applied for credit from any of those sources since the end of 2008 monsoon and was approved at least once.	2009 Baseline
Landholdings	Total area of agricultural land that belonged to the household as of the beginning of the Mrigashira kartis (June 8, 2009), in acres.	2009 Follow-Up

(*continued*)

Table A1
Continued

Variable	Descriptive information	Survey
Wealth index: PCA	First component of a principal component analysis (PCA). Variables includes a dummy if the household owns different specific types of livestock as well as the log total value of livestock, a dummy if the household has any type of credit, a dummy if the household has any type of savings, the log of total amount of savings and credit, the house type, the number of rooms in the house, the total area of agricultural land, the log of the house value, the log of the land value, and the log of the value of other assets.	2009 Baseline & 2009 Follow-Up
E. Land use and agricultural investments in 2009 monsoon		
All crops: Any ag. inputs used (1 = Yes)	Dummy variable equal to one if any agricultural inputs were used for the following categories: Hybrid seeds, improved seeds, fertilizer, manure, pesticide, irrigation, hiring tractors or other implements, manual labor, and bullock labor.	2009 Follow-Up
All crops: Total cultivated land, acres	Total cultivated land used towards all crops, in acres.	2009 Follow-Up
All crops: Market value of ag. inputs used, Rs.	Market value used on inputs (Rs.) towards all crops for the following categories: Hybrid seeds, improved seeds, fertilizer, manure, pesticide, irrigation, hiring tractors or other implements, manual labor, and bullock labor.	2009 Follow-Up
Cash crops: Any ag. inputs used (1 = Yes)	Dummy variable equal to one if any agricultural inputs were used for cash crops for only the following categories: Hybrid seeds, improved seeds, fertilizer, manure, and pesticide.	2009 Follow-Up
Cash crops: Total cultivated land, acres	Total cultivated land used towards cash crops, in acres.	2009 Follow-Up
Cash crops: Market value of ag. inputs used, Rs.	Market value used on inputs (Rs.) towards cash crops for only the following categories: Hybrid seeds, improved seeds, fertilizer, manure, and pesticide.	2009 Follow-Up
Share of total cultivated land devoted to cash crops	Share of total cultivated land used towards cash crops relative to total cultivated land used towards all crops.	2009 Follow-Up
Share of market val. of ag. inputs devoted to cash crops	Share of market value used on inputs towards cash crops for the categories of hybrid seeds, improved seeds, fertilizer, manure and pesticide relative to market value used on inputs towards all crops for those same categories.	2009 Follow-Up
F. Policy details		
Payout (Rs.)	Ex post payouts in Rupees. Reported in the text in units of 000s.	Admin Data

References

de Mel, S., D. McKenzie, and C. Woodruff. 2008. Returns to capital: Results from a randomized experiment. *Quarterly Journal of Economics* 123:1329–72.

Acemoglu, D., and F. Zilibotti. 1997. Was Prometheus unbound by chance? Risk, diversification, and growth. Journal of Political Economy 105:709–51.

Adelino, M., A. Schoar, and F. Severino. 2015. House prices, collateral and self-employment. *Journal of Financial Economics* 117:288–306.

Banerjee, A. V., and A. F. Newman. 1993. Occupational choice and the process of development. *Journal of Political Economy* 101:274–298

Beck, T., R. Levine, and N. Loayza. 2000. Finance and the sources of growth. *Journal of Financial Economics* 58:261–300.

Bertrand, M., and S. Mullainathan. 2001. Do people mean what they say? Implications for subjective survey data. *American Economic Review* 91:67–72.

Black, S. E., and P. E. Strahan. 2002. Entrepreneurship and bank credit availability. Journal of Finance 57: 2807–33.

Burgess, R., O. Deschenes, D. Donaldson, and M. Greenstone. 2013. The unequal effects of weather and climate change: Evidence from mortality in India. Working Paper, MIT.

Cai, H., Y. Chen, H. Fang, and L. Zhou. 2015. The effect of microinsurance on economic activities: Evidence from a randomized natural field experiment. *Review of Economics and Statistics* 97:287–300.

Campbell, J. 2006. Household Finance. *Journal of Finance* 61:1553–1604.

Campello, M., C. Lin, Y. Ma, and H. Zou. 2011. The real and financial implications of corporate hedging. *Journal of Finance* 66:1615–1647.

Carpenter, P., M. Just, and P. Shell. 1990. What one intelligence test measures: A theoretical account of the processing in the Raven Progressive Matrices test. *Psychological Review* 97:404–31.

Clarke, D. J. 2016. A theory of rational demand for index insurance. *American Economic Journal: Microeconomics* 8:283–306.

Clarke, D., O. Mahul, K. Rao, and N. Verma. 2012. Weather based crop insurance in India. World Bank Policy Research Working Paper 5985.

Cochrane, J. H. 1991. A simple test of consumption insurance. Journal of Political Economy 99:957–76.

Cole S., X. Giné, J. Tobacman, P. Topalova, R. Townsend, and J. Vickery. 2013. Barriers to household risk management: Evidence from India. *American Economic Journal: Applied Economics* 5:104–35.

Cole, S., A. Paulson, and G. Shastry. 2014. Smart money? The effect of education on financial outcomes. *Review of Financial Studies* 27:2022–51.

Dercon, S. 1998. Wealth, risk and activity choice: Cattle in western Tanzania. Journal of Development Economics 55:1–42.

Dercon, S., and L. Christiaensen. 2011. Consumption risk, technology adoption and poverty traps: Evidence from Ethiopia. Journal of Development Economics 96:159–73.

Duflo, E., M. Kremer, and J. Robinson. 2008. How high are rates of return to fertilizer? Evidence from field experiments in Kenya. *American Economic Review Papers and Proceedings* 98:482–88.

Emerick, K., A. de Janvry, E. Sadoulet, and M. H. Dar. 2016. Technological innovations, downside risk and the modernization of agriculture. *American Economic Review* 106:1537–61.

Fan, W., and M. J. White. 2003. Personal bankruptcy and the level of entrepreneurial activity. *Journal of Law and Economics* 46:543–567.

Fernández-Val, I. 2009. Fixed effects estimation of structural parameters and marginal effects in panel probit models. *Journal of Econometrics* 150:71–85.

Foster, A., and M. Rosenzweig. 2010. Microeconomics of technology adoption. *Annual Review of Economics* 2:395–424.

Froot, K. A., and J. C. Stein. 1998. Risk management, capital budgeting and capital structure policy for financial institutions: An integrated approach. *Journal of Financial Economics* 47:55–82.

Giné, X., L. Menand, R. Townsend, and J. Vickery. 2012. Microinsurance: A case study of the Indian rainfall index insurance market. In *Handbook of the Indian Economy*, ed. C. Ghate, 167–194. Oxford, UK: Oxford University Press.

Giné, X., R. Townsend, and J. Vickery. 2008. Patterns of rainfall insurance participation in rural India. *World Bank Economic Review* 22:539–566.

Giné, X., and D. Yang. 2009. Insurance, credit, and technology adoption: Field experimental evidence from Malawi. *Journal of Development Economics* 89:1–11.

Gollier, C., and J. W. Pratt. 1996. Risk vulnerability and the tempering effect of background risk. Econometrica 64:1109–23.

Guiteras, R. 2009. The impact of climate change on Indian agriculture. Working Paper, University of Maryland.

Hazell, P. B. R. 2009. Transforming agriculture: The green revolution in Asia. In *Millions Fed*, ed. D. Spielman, and R. Pandya-Lorch, 25–32. Washington, DC: IFPRI.

Hill, R. V., and A. Viceisza. 2012. An experiment on the impact of weather shocks and insurance on risky investment. *Experimental Economics* 15:341–371.

Hurst, E., and A. Lusardi. 2004. Liquidity constraints, household wealth, and entrepreneurship. *Journal of Political Economy* 112:319–47.

Jayachandran, S. 2006. Selling labor low: Wage responses to productivity shocks in developing countries. *Journal of Political Economy* 114:538–75.

Karlan, D., R. Osei, I. Osei-Akoto, and C. Udry. 2014. Agricultural decisions after relaxing credit and risk constraints. *Quarterly Journal of Economics* 129:597–652.

Karlan, D., A. Osman, and J. Zinman. 2016. Follow the money not the cash: Comparing methods for identifying consumption and investment responses to a liquidity shock. *Journal of Development Economics* 121:11–23.

King, R. G., and R. Levine. 1993. Finance, entrepreneurship and growth. *Journal of Monetary Economics* 32:513–42.

Levine, R. 2005.Finance and growth: Theory and evidence. In *Handbook of Economic Growth* 1, ed. P. Aghion, and S. Durlauf, 865–934, Elsevier.

Lybbert, T. J., F. B. Galarza, J. McPeak, C. B. Barrett, S. R. Boucher, M. R. Carter, S. Chantarat, A. Fadlaoui, A. Mude. 2010. Dynamic field experiments in development economics: Risk valuation in Morocco, Kenya, and Peru. *Agricultural and Resource Economics Review* 39:1–17.

Maccini, S., and D. Yang. 2009. Under the weather: Health, schooling and economic consequences of early-life rainfall. *American Economic Review* 99:1006–26.

Mobarak, A. M., and M. Rosenzweig. 2013. Selling formal insurance to the informally insured. Working Paper, Yale University.

Morduch, J. 1995. Income smoothing and consumption smoothing. *Journal of Economic Perspectives* 9:103–114.

Moskowitz, T. J., and A. Vissing-Jørgensen. 2002. The returns to entrepreneurial investment: A private equity premium puzzle? *American Economic Review* 92:745–78.

Pérez-González, F., and H. Yun. 2013. Risk management and firm value: Evidence from weather derivatives. *Journal of Finance* 68: 2143–76.

Pind, J., E. Gunnarsdottir., and H. Johannesson. 2003. Raven's Standard Progressive Matrices: New school age norms and a study of the test's validity. *Personality and Individual Differences* 34:375–86.

Puri, M., and R. Zarutskie. 2012. On the life cycle dynamics of venture-capital- and non-venture-capital-financed firms. *Journal of Finance* 67:2247–93.

Rampini, A., and S. Viswanathan. 2015. Household risk management. Working Paper, Duke University.

Raven, J. 2000. The Raven's Progressive Matrices: Change and stability over culture and time. Cognitive Psychology 41:1–48.

Rose, E. 1999. Consumption smoothing and excess female mortality in rural India. *Review of Economics and Statistics* 81:41–49.

Rosenzweig, M. R., and H. P. Binswanger. 1993. Wealth, weather risk and the profitability of agricultural investment. *Economic Journal* 103:56–78.

Rosenzweig, M. R., and O. Stark. 1989. Consumption smoothing, migration, and marriage: Evidence from rural India. Journal of Political Economy 97:905–26.

Skees, J. 2008. Innovations in index insurance for the poor in lower income counties. *Agricultural and Resource Economics Review* 37:1–15.

Townsend, R. 1994. Risk and insurance in village India. *Econometrica* 62:539–91.

Townsend, R., and K. Ueda. 2006. Financial deepening, inequality and growth: A model-based quantitative evaluation. *Review of Economic Studies* 73:251–293.

Walker, T. S., and J. G. Ryan. 1990. *Village and Household Economics in India's Semi-Arid Tropics*. Baltimore, MD: John Hopkins University Press.

World Bank. 2005. Managing agricultural production risk: innovations in developing countries. Washington, DC: World Bank Agriculture and Rural Development Department, World Bank Press.