Adaptation to Climate Change: Historical Evidence from the Indian Monsoon

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Abstract

There is a growing consensus that global temperature and precipitation patterns will change over the coming century, yet we have scant evidence on how agents will adapt to these new climate patterns. Existing estimates of climate change adaptation rely almost exclusively on extrapolation from cross-sectional variation, an approach that suffers from omitted variable bias and additionally relies on the assumptions of costless adaptation and of perfect knowledge of climate change. In this paper, I provide new and more reliable estimates of the ability of farmers to adapt to changes in their climate, based on evidence from historical variation in the intensity of the Indian monsoon. The Indian monsoon undergoes zonal and meridional regimes, in which droughts or floods are more common respectively, and these regimes last several decades. I find evidence that farmers adjust their irrigation investment and the water-intensiveness of their crop portfolio depending on which monsoon regime they currently face. Specifically, for a one standard deviation decrease in lagged decade mean rainfall, farmers increase their probability of investing in irrigation by 1.9 percentage points and increase the area planted to drought-tolerant crops by 2.1 percentage points. However, the ability of farmers to protect their profits via adaptation is limited: I find that only 15% of the profits lost due to harmful changes in the climate are recovered via adaptation.

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1 Introduction

There is a growing consensus among climate scientists that global temperature and precipitation patterns are changing and that these changes will accelerate over the coming century (Christensen and Hewitson, 2007). However, there is substantial uncertainty about what the total economic impacts of climate change will be. Estimates of the cost of a $2.5 - 3\,^{\circ}$C warming scenario range from a 1% gain of global GDP to a 4% loss of GDP. Regional impacts are even more uncertain, ranging, for example, from 3 to 23% loss of GDP for Africa, and from a 13% gain to a 9% loss for Asia (Tol 2009).[1] A major driver behind the uncertainty of economic impacts is uncertainty about adaptation: to what extent will agents in the economy be able to detect and respond to changes in the climate? Understanding the ability of agents to adapt is particularly crucial in developing countries and in the agricultural sector, as both are especially vulnerable to climate change (Hanson et al., 2007).

I estimate the extent to which farmers in India have adapted to historical, non-anthropogenic variations in their climate. The Indian monsoon undergoes phases in which droughts or floods are more common (known as zonal and meridional regimes, respectively), and these phases typically last for three to four decades. I test whether farmers in India have detected these medium-run variations in their climate and whether they have adapted their farm practices in response to them. I find evidence that farmers have adapted the water-intensiveness of their crop portfolio as well as their irrigation investment, in response to these variations of the monsoon. However, the impact on profits of the adaptation response is small: farmers are only able to recoup 14% of the losses due to harmful variations in their climate.

This paper is related to two strands of literature: first, the literature that estimates the economic impacts of climate change, and second, the literature that estimates how agents will adapt to climate change. Regarding the literature on economic impacts, most studies rely on one of three methodologies. In the *crop modeling approach*, researchers use data from controlled experiments (in, for example, greenhouses), to study the effect of increased temperatures on crop yields. This approach assumes zero adaptation: it does not allow for the fact that farmers might alter their crop choice or agricultural inputs in response to the increased temperatures. In the *Ricardian approach*, researchers estimate a cross-sectional correlation between climate and farmland prices and then use this corre-

[1] Note that these warming scenarios include both the changes in temperature and the associated changes in precipitation, which are variable across the globe. Furthermore, as Tol acknowledges in his survey paper, there are no estimates for the total economic cost of a change in climate that exceeds $3\,^{\circ}$C warming, despite the fact that much larger increases in temperature are possible.

lation to derive climate change impacts. The Ricardian approach assumes instantaneous and costless adaptation: it does not allow for financial or informational barriers to adaptation. Lastly, in the *panel approach*, researchers estimate climate change impacts using year-to-year variations in the weather. Similarly to the crop modeling approach, the panel approach assumes zero adaptation. In the context of India, Khan et al. (2009) is an example of the crop modeling approach, Sanghi and Mendelsohn (2008) is an example of the Ricardian approach, and Guiteras (2009) and Burgess et al. (2011) are examples of the panel approach.

This paper is also related to the literature on adaptation to climate change. The existing literature on adaptation relies primarily on the Ricardian approach. In this approach, researchers estimate a cross-sectional relationship between agricultural practices and climate, and then use this cross-sectional relationship to predict how farmers will adjust their agricultural practices under anthropogenic climate change. Papers using this methodology have studied farm type (Seo and Mendelsohn, 2008b), livestock choice (Seo et al., 2010), crop choice (Seo and Mendelsohn, 2008a) and irrigation (Fishman, 2011; Kurukulasuriya et al., 2011). However, Ricardian estimates of adaptation suffer from several problems. First, since they rely on cross-sectional variation, these estimates suffer from a potential omitted variable problem: if unobserved factors, such as soil quality, market institutions, or infrastructure are correlated with cross-sectional variation in climate, then estimates will be biased.[2] A second issue is that Ricardian estimates are based on how farmers have adapted to a stationary climate that they (and their ancestors) have faced for centuries. Hence the estimates may be of limited applicability to the situation of a climate that is varying over time. In particular, Ricardian estimates can tell us nothing about the speed of adaptation. Furthermore, the Ricardian approach will give upwardly biased estimates of adaptation in the (highly likely) case that there are financial and informational barriers to adaptation. For this reason, Ricardian estimates of adaptation are most appropriate for the very long-run, once a new stable climate has been reached, and they are less informative for the short-run and medium-run, during which farmers are on the transition path to a new climate.

The principal contribution of this paper is that I construct estimates of climate change adaptation that do not rely on cross-sectional climate variation, but instead are based on how farmers have adapted to actual, historical changes in India's climate. Figure 1 shows the 31-year moving average of the all-India summer monsoon rainfall. As can be seen in the graph, there were two periods where the rainfall for all of India was above its his-

[2] Since these papers often use data on farmers across several different countries with widely varying institutions, infrastructure and geography, the magnitude of the omitted variable bias could be severe.

torical average, roughly from 1870 to 1900 and again during 1930 to 1970, and two complementary periods during which rainfall was below its historical average. The existence of these rainfall regimes means that for a given farmer, annual rainfall is not i.i.d. Rainfall realizations from the last decade or so give the farmer some information about what the rainfall over the coming decade will be. Importantly for my identification strategy, there is spatial variation in the timing of these rainfall regimes, as can be seen from Figure 2, which replicates Figure 1 for the five meteorological regions of India. I test whether farmers are adapting to the regime-based variation in their climate, by analyzing whether their agricultural assets and crop portfolios respond to lagged weather. I exploit the fact that the return to irrigation investment varies across wet versus dry growing seasons and that similarly, the relative yields of different crops vary across wet versus dry growing seasons. My empirical strategy is to test whether irrigation assets and crop portfolios respond to lagged weather, while controlling for wealth, household fixed effects and year fixed effects. The household fixed effects allow me to control for omitted variables such as soil quality, institutions, infrastructure, and unobserved farmer ability. The year fixed effects allow me to separate adaptation effects from smooth time trends in irrigation and crop choice. I am able to include the year fixed effects due to the spatial variation in the timing of the rainfall regimes.

This paper has two key advantages over the previous literature. First of all, I use panel data on agricultural households, and hence I eliminate the omitted variable bias that contaminates Ricardian estimates of adaptation. Secondly, because I measure adaptation to a climate that is varying over time, my approach takes into account informational and financial barriers to adaptation. A related paper that also estimates how economic agents have responded to time-varying changes in their climate is Hornbeck (2009), which studies how farmers adapted to the Dust Bowl, a sudden and severe period of drought and soil erosion that affected the US Midwest in the 1930's. Hornbeck finds that adaptation was severely limited and that people primarily adapted by migrating out of the area. This is an interesting result, however because the Dust Bowl was so sudden and severe, the results are of limited applicability to anthropogenic climate change, since most places will experience small changes in their climate. The current paper has the advantage of measuring adaptation to marginal changes in climate, rather than catastrophic changes. Furthermore, Hornbeck is not able to explicitly separate farmers expectations of future climate from their response to (already realized) soil erosion. In contrast, I am able to explicitly test whether farmers are updating their expectations of future climate, based on lagged realizations of climate.

I model the Indian monsoon as a hidden Markov model, where the regime type (wet or dry) is the unobserved state variable, and growing season rainfall is the observed output variable. I combine this climate model with a simple, dynamic, two-period agricultural model of irrigation investment and crop choice. I am interested in testing whether farmers are updating their expectations of future rainfall, in response to past rainfall. I do not have explicit information on farmer's expectations of the weather, however I develop two sets of conjectured tests for updated expectations, using farmers' actions in irrigation investment and crop choice.

I use two agricultural datasets in this paper. The first is a panel household data set from the ARIS-REDS survey conducted by the NCAER, which covers over 8000 households over the crop seasons 1970/71, 1981/82 and 1998/99. The second agricultural data set is a district level data set collected by researchers at the World Bank, covering 271 districts for the years 1956-1987. I merge these agricultural data sets with a gridded monthly rainfall and temperature data set from the University of Delaware that covers the years 1900-2008.

In both data sets, I find evidence that farmers do indeed adapt their irrigation investment and their crop portfolio in response to variations in the monsoon rainfall regimes. Specifically, controlling for wealth, farmers invest more in irrigation following decades that have been particularly dry. And, also controlling for wealth, they plant more area to drought-tolerant crops following decades that have been particularly dry. In terms of magnitudes, for a one standard deviation decrease in lagged decade mean rainfall, farmers increase their probability of investing in irrigation by 1.9 percentage points and increase the area planted to drought-tolerant crops by 2.1 percentage points. However, when I estimate the impact on profits of adaptation, I find that the effect is small: farmers are only able to recoup 15% of the losses that they faced due to negative climate changes.

There are some important caveats to take note of regarding both the adaptation outcomes that I consider, and the variation in climate that I use. I consider the adaptation outcomes of irrigation investment and crop choice: however there are both larger-scale adaptations possible (such as migrating or switching out of agriculture), as well as smaller-scale adaptations possible (such as adjusting fertilizer usage or altering sowing date). Due to data limitations, I cannot say anything about these other types of adaptation. The other important caveat is that there has been historical variation in the precipitation of India, but not the temperature, so I can say something about adaptation to changes in precipitation, but nothing about adaptation to changes in temperature.

The results of this paper have several important policy implications. The finding that farmers recover only a comparatively small amount (15%) of the losses due to harmful climate change, suggests that there may be significant financial and informational barriers to adaptation. Financial barriers are likely substantial in the case of irrigation investment, if credit constraints inhibit households from investing optimally in irrigation. Informational barriers, such as learning about new crops, may inhibit households from choosing an optimal crop portfolio. Therefore policies that alleviate these barriers may help farmers adapt to future, anthropogenic climate change.

The rest of the paper proceeds as follows. In Section 2, I provide background information about the monsoon rainfall regimes in India. I also provide some background information on the crop choice parameters that I will be studying. Section 3 lays out a theoretical model of climate, irrigation investment and crop choice. Section 4 describes the data I will use to test empirically the predictions of the model and provides some summary statistics of key variables. Section 5 explains my empirical strategy. I present my results in section 6. In Section 7, I estimate the extent to which adaptation has protected agricultural profits in my historical sample; I also present projections for adaptation under a counterfactual climate change scenario. Section 8 concludes.

2 Background

2.1 Interdecadal Variability of the Indian Monsoon

Indian agriculture relies heavily on the vagaries of the summer monsoon (Binswanger and Rosenzweig, 1993; Krishna Kumar et al., 2004). The Indian monsoon arrives in the state of Kerala in May, and spreads over the entire country in the months of summer. Typically, excess monsoons are considered to be good for agricultural profits, and deficient monsoons are considered to be bad for agriculture (Das, 1995). In addition to exhibiting year-to-year variability, the monsoon of India also exhibits variability on an inter-decadal time span. Specifically, there are certain decades when the rainfall for all of India is above its historical average, and other decades when rainfall is below its historical mean. Meteorologists refer to these periods as meridional and zonal regimes, respectively (Pant and Kumar, 1997; Wang, 2006). Figure 1 shows the 31-year moving average of the all-India summer monsoon rainfall from 1871 (the start of the instrumental record) to present. As can be seen in the graph, there were two periods where the rainfall for all of India was above its historical average, roughly from 1870 to 1900 and again during 1930 to 1970, and two complementary periods during which rainfall was below its historical average.

Figure 3 shows the summer rainfall for each year, with the wet (meridional) regimes shaded gray. According to the meteorological literature, year-to-year rainfall in India is not i.i.d, but instead switches back and forth between wet and dry regimes, due to an atmospheric-oceanic feedback mechanism (Wang, 2006). Hence, instead of facing a single distribution of rainfall, as in Figure 4, farmers in India actually face two different distributions of rainfall, depending on what the current rainfall regime is, as displayed in Figure 5. In any given year, there is uncertainty about what the current rainfall regime is. Therefore, a farmer's expectation of the next year's rainfall will vary over time, depending on what rainfall regime is believed to be faced.

More precisely, we can treat the monsoon as a hidden Markov model, where the unobserved state variable is regime type (wet or dry) and the observed output variable is annual rainfall. Wet and dry regimes have different rainfall means. In each period, there is a certain probability of transitioning to the other type of regime. Farmers know the parameters of the rainfall distribution but they don't know the state variable. Hence, lagged rainfall shocks give farmers information about the current regime that they face.

Although the meteorological literature agrees that the rainfall of India undergoes rainfall regimes that vary over time, I was not able to find any meteorological papers that tested for the statistical significance of the rainfall regimes. In particular, it is important to know whether the inter-decadal variability of the India monsoon is greater than what would be expected if the rainfall was i.i.d.[3] To address this question, I test for the existence of two rainfall regimes, against the null hypothesis of a single regime, using the quasi-likelihood ratio test developed in Cho and White (2007). The distribution of the test statistic is non-standard due to nuisance parameters that only exist under the alternative hypothesis; however I am able to use the critical values tabulated in Steigerwald and Carter (2011) for this purpose. I calculate the test statistic to be 9.61, which is greater than the tabulated 5% critical value of 5.54, and hence I am able to reject the null hypothesis of a single regime.

A final important point regarding the monsoon regimes is that there are significant spatial variations, across India's thirty different meteorological subdivisions, in the relative lengths and timings of the wet and dry regimes (Subbaramayya and Naidu, 1992). Specifically, the rainfall over the easternmost part and the southern tip of the country tend to go out of phase with the rest of the country (Wang, 2006). This is important for my identification strategy, as it will allow me to identify adaptation to the rainfall regimes separately from smooth time trends in irrigation and crop choice. Figure 2 shows the rainfall graphs for all India, as well as for the five meteorological regions. As can be seen from

[3] If rainfall was actually i.i.d., then lagged rainfall shocks would not give farmers any information about future rainfall. Therefore, it would be irrational from farmers to adjust their expectations and their farm practices in response to lagged rainfall (e.g. it would be an example of the hot hand fallacy). Hence, demonstrating that rainfall is not i.i.d. is important for determining the correct interpretation of my empirical results.

the figure, the timing of the regimes varies across the different regions. In particular, the rainfall for the peninsula region is out of phase with the rest of the country.

2.2 Historical Variation of Summer Mean Temperature for India

Since both temperature and precipitation patterns will change for India under future anthropogenic climate change, it would be desirable to estimate adaptation to temperature as well as precipitation. Unfortunately, there is insufficient historical variation in temperature for me to be able to apply the approach I use with precipitation. Figure 6 shows the 31-year moving average of the all India summer mean temperature. Unlike the corresponding graph for precipitation, summer mean temperature does not exhibit statistically significant regime-switching behavior. Temperature does exhibit a warming trend, starting roughly in 1965. Note that the magnitude of the warming (roughly 0.1 °C per decade), is half of the magnitude of the rate of warming predicted for the medium-run (2010-2039) and a quarter of the rate of warming predicted by the end of the century under business as usual scenarios. However, I cannot test for adaptation due to this temperature trend, because, unlike the precipitation regimes, there is insufficient cross-sectional variation in the warming. Hence, it is impossible to separate out historical adaptation to temperature trends from other smooth time trends, such as changes in technology.

2.3 Background on Crop Choice

Before presenting the model, I now provide a bit of background relating to the crop choice parameters that I will be studying. According to agronomists at FAO, when studying the water-intensiveness of different crops, there are two relevant (and distinct) parameters to consider: crop water need and sensitivity to drought. The water need of a crop is defined as the amount of water a given crop needs for optimal growth, and is typically defined as a range, expressed in total millimeters of rainfall per the growing season. A crop's sensitivity to drought is defined as how much a crop's yield is diminished if it doesn't receive its water requirement. Table 1 presents these two parameters for the major crops of India. As can be seen from the table, the two parameters are distinct and not tightly correlated. For example, cotton and sugarcane both have relatively high water needs, however cotton exhibits a low-sensitivity to drought, whereas sugarcane is highly drought-sensitive. Similarly, rice and sorghum both have moderate water needs relative to other crops of India, but rice is highly sensitive to drought whereas sorghum is drought-tolerant.[4]

[4]Note that I am comparing the drought sensitivities across broad crop categories, such as rice and sorghum. I am not looking at drought sensitivities within, say, different varieties of rice.

3 Theoretical Framework

In this section, I present a formal model of the monsoon rainfall regimes. I then develop a simple, dynamic two-period agricultural model of irrigation investment and crop choice. Lastly, based on the climate and agriculture models, I describe two sets of conjectured tests that can be used for testing whether farmers are adapting to variation in the monsoon rainfall regimes.

3.1 Climate

I develop a model in which the monsoon rainfall follows a hidden Markov model. Let growing season rainfall in year t, r_t, be given by

$$r_t = \theta_0 + \delta S_t + U_t \tag{1}$$

where $U_t \sim i.i.d.N(0, \nu)$.[5] The unobserved state variable $S_t \in \{0, 1\}$ indicates regimes, with $S_t = 0$ corresponding to a dry regime, and $S_t = 1$ corresponding to a wet regime, and $\delta > 0$. Furthermore, the sequence $\{S_t\}_{t=1}^{T}$ is generated as a first-order Markov process with $\Pr(S_t = 1 \mid S_{t-1} = 0) = p_0$ and $\Pr(S_t = 0 \mid S_{t-1} = 1) = p_1$. Hence the mean rainfall during a dry regime is θ_0 and the mean rainfall during a wet regime is $\theta_1 = \theta_0 + \delta$.

I assume that farmers know all the climate parameters (e.g. θ_0, δ, ν, p_0 and p_1) and that they observe r_t but that they do not observe S_t.[6] For modeling purposes, I assume that the Markov process is duration-independent, in other words that the probability of switching to the other regime type depends only on the current regime, not how long you have been in the current regime.

3.2 Irrigation and Crop Choice

I develop a simple two-period model of irrigation investment and crop choice. In period t, a farmer has wealth w_t which he can allocate between an irrigation asset i_t and another agricultural (non-irrigation) asset a_t, such that $a_t + i_t = w_t$. I assume that there are no credit markets and no non-agricultural assets. The farmer has one unit of land, on which he plants a proportion ρ_t to a drought-tolerant crop and $1 - \rho_t$ to a drought-neutral crop. The profit function for a farmer is given by:

[5] The growing season rainfall is for location j, e.g. either a specific village or a specific district. I drop the subscript j for notational simplicity, but the variables R_t, θ_0, δ, S_t, U_t and ν all vary at the local level.

[6] Theoretically, a farmer could know about rainfall at other locations and use this to develop his predictions about the current regime type, but I abstract away from this possibility.

$$\pi_t = \beta_a a_t + \beta_i i_t + \beta_\rho \rho_t + \frac{1}{2}\delta_{aa} a_t^2 + \frac{1}{2}\delta_{ii} i_t^2 + \delta_i i_t r_t + \delta_\rho \rho_t r_t + \delta_r r_t + \epsilon_t \tag{2}$$

where π_t is profits per acre, and ϵ_t is a mean zero productivity shock. In order to develop my tests for adaptation, I need to make several assumptions about the coefficients of the profit function. I will test these assumptions in the empirical part of the paper. Specifically I need to assume the following coefficient signs:

- Return to rainfall: assume $\delta_r > 0$. I need the assumption that profits are higher during wet years than they are during dry years. This is generally agreed upon for the literature in India (see, for example, Jayachandran (2006)). Additionally, I test this empirically in Section 6.1.

- Return to irrigation: assume $\delta_i < 0$. I need the assumption that the return to irrigation is higher during dry years than it is during wet years. Again, I test this empirically in Section 6.1.

- Return to crop choice: assume $\delta_\rho < 0$. I need the assumption that the return to planting drought-tolerant crops is higher during dry years than it is during wet years. This follows from the definition of being drought-tolerant.

Given the above profit function, a farmer maximizes $u(c_1) + \beta E_1[u(c_2)]$, where $0 < \beta < 1$, subject to the budget constraints $c_1 + w_2 = w_1 + \pi_1$ and $c_2 = w_2 + \pi_2$. I assume that the farmer's utility function exhibits decreasing relative risk-aversion.

The timing of the model is as follows:

1. First, farmer chooses i_1 and ρ_1, given w_1, $E_0[r_1]$ and $E_0[r_2]$.

2. Then, r_1 and π_1 are realized.

3. Then, the farmer chooses c_1 and w_2, given $w_1 + \pi_1$ and $E_1[r_2]$.

4. Then, the farmer chooses i_2 and ρ_2, given w_2 and $E_1[r_2]$.

5. Lastly, r_2 and π_2 are realized.

The model can be solved using the Euler equation: $u'(c_1) = \beta E_1[u'(c_2)]$. That is to say, the optimal consumption decision will equate the marginal utility of first-period consumption with the expected marginal utility of second-period consumption. The optimal second-period irrigation and crop choice decisions can be written as $i_2^*(w_2, E_1(r_2))$ and $\rho_2^*(w_2, E_1(r_2))$. Furthermore, the optimal second-period wealth decision can be written as: $w_2^*(w_1, E_0[r_1], r_1, E_1[r_2])$. I have not yet solved explicitly for these expressions.

3.3 Testing for Adaptation to Climate Change

Given the above model and the above assumptions, I can develop some tests to see whether farmers are adapting to changes in their climate. Specifically, I want to test whether $\frac{dE_1(r_2)}{dr_1} > 0$ or $\frac{dE_1(r_2)}{dr_1} = 0$. Can we infer whether farmers are updating their rainfall expectations by looking at the response of irrigation (or crop choice) to lagged rainfall? I first discuss the case for irrigation, and then for crop choice.

3.3.1 Testing for Adaptation via Irrigation Investment

I am interested in whether we can infer that farmers are updating their rainfall expectations by looking at the response of irrigation to lagged rainfall. Note that:

$$\begin{aligned}
\frac{di_2^*}{dr_1} &= \frac{\partial i_2^*}{\partial w_2^*}\frac{dw_2^*}{dr_1} + \frac{\partial i_2^*}{\partial E_1(r_2)}\frac{dE_1(r_2)}{dr_1} \\
&= \frac{\partial i_2^*}{\partial w_2^*}\left[\frac{\partial w_2^*}{\partial r_1} + \frac{\partial w_2^*}{\partial E_1(r_2)}\frac{dE_1(r_2)}{dr_1}\right] + \frac{\partial i_2^*}{\partial E_1(r_2)}\frac{dE_1(r_2)}{dr_1}
\end{aligned}$$

Rearranging terms, we get:

$$\frac{di_2^*}{dr_1} = \underbrace{\frac{\partial i_2^*}{\partial w_2^*}\frac{\partial w_2^*}{\partial r_1}}_{\text{wealth effect}} + \underbrace{\left[\frac{\partial i_2^*}{\partial w_2^*}\frac{\partial w_2^*}{\partial E_1(r_2)} + \frac{\partial i_2^*}{\partial E_1(r_2)}\right]}_{\text{expectations effect}}\frac{dE_1(r_2)}{dr_1}$$

Therefore, the total derivative of second period irrigation with respect to first period rainfall can be written as the sum of a wealth effect and an expectations effect. For irrigation investment, I conjecture that the wealth effect term is positive and that the expectations effect term is negative. Specifically, for the wealth effect term: more rainfall in the first period means that farmers have more wealth, which means they should invest more in all assets, including irrigation. However, the expectations effect goes in the opposite direction: more rainfall in the first period means that farmers expect higher rainfall in the second period, which means they should invest less in irrigation (since the return to irrigation is lower during wet years).

Based on these (conjectured) signs of the wealth and expectation effects, I can develop two tests for whether farmers are updating their expectations of rainfall.

- Conjectured Irrigation Test 1 (Unconditional): If farmers invest more in irrigation after a low rainfall realization, this implies they are updating their rainfall expectations.

– Specifically, if $\frac{di_2^*}{dr_1} < 0$, then $\frac{dE_1(r_2)}{dr_1} > 0$.

- Conjectured Irrigation Test 2 (Conditional on wealth): If, conditional on wealth, farmers invest more in irrigation after a low rainfall realization, this implies they are updating their rainfall expectations.

  – Specifically, if $\left.\frac{di_2^*}{dr_1}\right|_{w_2^*=constant} < 0$, then $\frac{dE_1(r_2)}{dr_1} > 0$.

3.3.2 Testing for Adaptation via Crop Choice

I am also interested in whether we can infer that farmers are updating their rainfall expectations by looking at the response of crop choice to lagged rainfall. I can take the total derivative of second period crop choice with respect to first period rainfall. If I again apply the chain-rule and rearrange terms, I get the following expression:

$$\frac{d\rho_2^*}{dr_1} = \underbrace{\frac{\partial \rho_2^*}{\partial w_2^*}\frac{\partial w_2^*}{\partial r_1}}_{\text{wealth effect}} + \underbrace{\left[\frac{\partial \rho_2^*}{\partial w_2^*}\frac{\partial w_2^*}{\partial E_1(r_2)} + \frac{\partial \rho_2^*}{\partial E_1(r_2)}\right]}_{\text{expectations effect}}\frac{dE_1(r_2)}{dr_1}$$

For crop choice, I conjecture that both the wealth effect term and the expectations effect term are negative. For the wealth effect: more rainfall in the first period means that the farmer has more wealth, which means that the farmer is less risk-averse, which means the farmer should plant less area to the drought-tolerant crop. For the expectations effect: more rainfall in the first period means that the farmer expects higher rainfall in the second period, which means that the farmer should plant less area to the drought-tolerant crop (since it has a lower return during wet years).

Based on these (conjectured) signs of the wealth and expectation effects, I can develop one test for whether farmers are updating their expectations of rainfall.

- Conjectured Crop Choice Test 1 (Conditional on wealth): If, conditional on wealth, farmers plant more to drought-tolerant crops after a low rainfall realization, this implies they are updating their rainfall expectations.

  – Specifically, if $\left.\frac{d\rho_2^*}{dr_1}\right|_{w_2^*=constant} < 0$, then $\frac{dE_1(r_2)}{dr_1} > 0$.

4 Data Sources and Summary Statistics

4.1 Data

My first agricultural data set comes from the Additional Rural Incomes Survey (ARIS) and the Rural Economic and Demographic Survey (REDS), both of which were collected by the National Council of Applied Economic Research (NCAER) in Delhi. The ARIS/REDS dataset is a panel household dataset that covers the agricultural years 1970/71, 1981/82 and 1998/99. The survey collects detailed data on agricultural outcomes, including assets, inputs, and profits. The 1971 round covers approximately 4500 households in over 250 villages across 17 states of India. The 1982 round covers approximately 5000 households, of which roughly two thirds are the same as from the 1971 round. The 1999 round covers approximately 7500 households. The 1999 round includes all households from 1982 (including households that split off from the original 1982 households), as well as some new households.[7]

I also use a district-level agricultural dataset, the "India Agriculture and Climate Data Set" which was collected by a World Bank research group (Sanghi et al., 1998). This data set compiles detailed district-level data from the Indian Ministry of Agriculture and other official sources, and it includes outcome variables such as yearly agricultural production, output prices and acreage planted and cultivated for 271 districts across 14 states, covering 85% of India's area. The dataset covers the crop years from 1956/57 to 1986/87, with annual frequency. The dataset is missing several of the outcome variables covered by the ARIS/REDS dataset, including agricultural assets, inputs and profits.[8] However, I am able use agricultural yields in place of profits. And, the dataset does have data on irrigated area, and proportion of area planted to different crops.

For weather data, I merge the agricultural datasets with a monthly rainfall dataset that is constructed on a 0.5° latitude by 0.5° longitude grid. The rainfall data set, Terrestrial Precipitation: Monthly Time Series (1900-2008), version 2.01, was constructed by Kenji Matsuura and Cort J. Willmott (with support from IGES and NASA) at the Center for Climatic Research, University of Delaware. The rainfall measure for a latitude-longitude grid point combines data from 20 nearby weather stations using an interpolation algorithm based on the spherical version of Shepards distance-weighting method. I use the rainfall from the grid point nearest to each village in the ARIS/REDS dataset. For the

[7]Because my empirical strategy relies on dynasty fixed effects (see Section 5), I only use households that are members of dynasties that are interviewed in at least two of the three rounds. (I am able to include both panel households and households that split off from panel households.)

[8]The dataset does have some limited data on assets and inputs, but they are unreliable.

district data set, I use the rainfall from the grid point nearest to the district center.[9]

For my rainfall measure, I use growing season rainfall, which I define as the sum of rainfall for June through September for most of the country (which corresponds to the main summer monsoon) and which I define as the sum of rainfall for June through December for the states of Tamil Nadu and Andhra Pradesh (which corresponds to both the main summer monsoon and the winter monsoon, which impacts these states the most, following the state-specific rainfall monthly charts in Pant and Kumar (1997)).

4.2 Summary Statistics

Table 2 gives summary statistics for the ARIS/REDS dataset. As can be seen from the table, farm profits per acre are increasing over time for the period 1971 to 1999, as is the proportion of irrigated land.

Table 3 gives summary statistics for the World Bank dataset. In this dataset, proportion of land irrigated is also increasing over time. Note that the World Bank data set does not have a measure of agricultural profits. Instead, I follow Jayachandran (2006) and construct the variable log crop yield to be the weighted average of log(volume of crop produced/area cropped) for the five major crops by revenue.[10]

5 Empirical Strategy

In this section, I outline my empirical strategy. I begin with my strategy for estimating the return to irrigation, and then I describe my strategies for testing whether farmers are adapting their irrigation investment and their crop portfolio to variations in the monsoon regimes.

5.1 Return to Irrigation

Let π_{ijt} represent agricultural profits per acre for farmer i, in village j, in year t. I estimate a profit function of the form:

[9] I also control for temperature in some of the regressions that I run. I use the companion temperature data set Terrestrial Air Temperature: 1900-2008 Gridded Monthly Time Series, version 2.01, which was constructed by the same researchers and using the same methodologies.

[10] The five major crops by revenue are rice, wheat, sugar, sorghum, and groundnuts. The weights are the district average revenue share of the crop. I normalize the yield for each crop has been normalized to mean one for comparability across crops.

$$\pi_{ijt} = \beta_1 rain_{jt} + \beta_2 propirr_{ijt} + \beta_3 rain_{jt} * propirr_{ijt} + nonlandwealth_{ijt} + \\ + temperature_{jt} + year_t + farmer_{ij} + \epsilon_{ijt} \quad (3)$$

where $rain_{jt}$ is the deviation of current growing season rainfall for the village from its historical mean, expressed as a z-scores, and $propirr_{ijt}$ is the proportion of the farmer's land that is irrigated. The term $nonlandwealth_{ijt}$ represents the non-land wealth of the farmer and the term $temperature_{jt}$ represents the mean growing season temperature in the village that year, expressed as a z-score deviation from its historical mean. The term $year_t$ is a year fixed effect that controls for nation-wide year specific shocks, as well as any longer-term nation-wide trends. The term $farmer_{ij}$ is a farmer fixed effect that controls for any time-invariant unobserved farmer ability that may be correlated with both $profit_{ijt}$ and $propirr_{ijt}$.[11] Additionally, I instrument for $propirr_{ijt}$ with the proportion of inherited land that was irrigated. This instrumental variables strategy alleviates two potential concerns. The first concern is that farmers who have higher ability will adopt irrigation earlier, and that this will not be captured by the farmer fixed effect. The second concern is that unobserved (non-weather) shocks, such as health shocks, could be an omitted variable that affects both $propirr_{ijt}$ and $profit_{ijt}$. Both of these concerns are allayed by instrumenting with proportion of inherited land that was irrigated .

Based on the assumptions outlined in Section 3.2, I expect $\beta_1 > 0$ (profits are higher in wet years than in dry years) and $\beta_3 < 0$ (the return to irrigation is higher in dry years than in wet years). Additionally, I expect that $\beta_2 > 0$ (having irrigation increases profits, independent of rainfall).

5.2 Testing for Adaptation via Irrigation Investment

I next estimate a regression to see how the proportion of land irrigated responds to lagged rainfall shocks, and specifically to test whether farmers are adapting their irrigation investment in response to the rainfall regimes. I run a regression of the form:

$$irr\_inv_{ijt} = \alpha_1 decaderain_{jt} + \alpha_2 L.rain_{jt} + year_t + farmer_{ij} + \epsilon_{ijt} \quad (4)$$

where irr_inv_{ijt} is a dummy variable for whether the household invested in irriga-

[11]Since the household head may change across survey rounds, and the household may split into additional households, the farmer fixed effect is really best thought of as a dynasty fixed effect that controls for unobserved agricultural ability that is common to all parts of the dynasty.

tion during the survey year.[12] The term $decaderain_{jt}$ is the average rainfall over the past decade. I control for one-year-lagged rainfall, $L.rain_{jt}$, because of the possible concern that last year's rainfall might directly affect the decision to invest in irrigation directly, not through expectations of future weather.[13] The year fixed effect controls for nation-wide time trends in irrigation investment. The farmer fixed effect controls for time-invariant factors (such as soil-quality) that might affect the household's decision to invest in irrigation. The coefficient of interest is α_1: specifically, is a household more likely to invest in irrigation following especially wet decades or following especially dry decades? My model is ambiguous about the sign of α_1 in this regression: if the wealth effect dominates, then $\alpha_1 > 0$; but if the adaptation effect dominates, then $\alpha_1 < 0$. Finding a negative coefficient demonstrates that farmers are adapting to the changes in their climate.

I also run another specification in which I control for non-land wealth:

$$irr\_inv_{ijt} = \alpha_1 decaderain_{jt} + \alpha_2 L.rain_{jt} + nonlandwealth_{ijt} + year_t + farmer_{ij} + \epsilon_{ijt} \quad (5)$$

In this regression, the model unambiguously predicts that $\alpha_1 < 0$. In other words, since I am controlling for wealth, the coefficient on α_1 is purely due to adaptation. In this regression, there is a concern that non-weather shocks, such as health shocks, might affect both $nonlandwealth_{ijt}$ and irr_inv_{ijt}. Therefore, I use inherited non-land wealth as an instrument for $nonlandwealth_{ijt}$.[14]

5.3 Testing for Adaptation via Crop Choice

I next estimate regressions to see how a farmer's crop portfolio responds to lagged rainfall shocks, and specifically to test whether farmers are adapting their crop portfolio in response to the rainfall regimes. As described in Section 2.3, I have two crop parameters of interest: crop water requirement (the amount of water a specific crop needs to grow optimally), and crop sensitivity to drought (how much a crop's yield is diminished if its optimal water requirement is not met). I use the crop water requirements and drought sensitivities given in a FAO manual (Brouwer and Heibloem, 1986), as reproduced in Ta-

[12] For the district-level data set I don't have data on irrigation investment explicitly, so I use the one-year change in the net irrigated area of the district as the dependent variable.

[13] This could happen if last year's rainfall continues to affect soil moisture in the following year.

[14] I am able to use this instrument at the same time that I use the farmer fixed effects, due to the household splits. E.g. some parts of the dynasty have different inherited wealth. Also, I use non-land wealth because land markets in India are very inactive, so land prices are unreliable, and land wealth is not easily converted into other forms of wealth.

ble 1. Crop water needs are given in millimeters per growing season; drought sensitivity is a discrete variable with four categories: low, low-medium, medium-high, or high. From the values in the table, I construct three different measures of the water-intensiveness of a farmer's crop portfolio: $water\_need_{ijt}$, $area\_tolerant_{ijt}$ and $area\_sensitive_{ijt}$. The variable $water\_need_{ijt}$ is defined as area-weighted average water need of the farmer's crop portfolio.[15] The variable $area\_tolerant_{ijt}$ is defined as the proportion of cultivated area that is planted to crops with low drought sensitivity. And similarly, the proportion of cultivated area that is planted to crops with high drought sensitivity is called $area\_sensitive_{ijt}$.[16]

I run regressions with all three of these outcome variables, to test whether they respond to lagged rainfall. Specifically, I run regressions of the form:

$$crop\_var_{ijt} = \alpha_1 decaderain_{jt} + \alpha_2 rain_{jt} + nonlandwealth_{ijt} + year_t + farmer_{ij} + \epsilon_{ijt} \quad (6)$$

where $crop\_var_{ijt}$ is $water\_need_{ijt}$, or $area\_tolerant_{ijt}$, or $area\_sensitive_{ijt}$. As above, $decaderain_{jt}$ measures the average rainfall of the previous decade. I control for current year rainfall because farmers may have some knowledge of the current year rainfall (e.g. the monsoon start date) before they choose which crops to plant.[17] Since the adaptation effects and wealth effects go in the same direction for crop choice (see Section 3.3.2), I control for $nonlandwealth_{ijt}$ in all regressions. And again, I instrument for non-land wealth with inherited non-land wealth, to alleviate the concern that unobserved, non-weather shocks, such as health shocks, might affect both $nonlandwealth_{ijt}$ and $crop\_var_{ijt}$. Conditional on wealth, the model unambiguously predicts that $\alpha_1 > 0$ for $water\_need_{ijt}$ and $area\_sensitive_{ijt}$, and that $\alpha_1 < 0$ for $area\_tolerant_{ijt}$. In other words, if farmers are adapting to change in their climate, they should plant a crop portfolio that requires more water, if recent years of rainfall have been above average. Additionally, farmers should plant more area to crops that are drought sensitive, if recent years of rainfall have been above average. And lastly, farmers should plant less area to crops that are drought sensitive,

[15] Crop water needs are given as a range in the FAO table; I use the median of the range for each crop, when constructing $water\_need_{ijt}$

[16] Note that sugarcane is almost exclusively irrigated (98% of area in the 1999 REDS round, for example). But sugarcane also has a much higher water need than most of the crops grown in India. For this reason, when constructing the crop choice variables, I exclude sugar cane from the calculations.

[17] Accordingly to evidence from Binswanger and Rosenzweig (1993), the monsoon start date is the most important factor for determining crop profits. Hence, there might be some concern that farmer should just use the monsoon start date to determine what crops to plant, and not use the decade lagged rainfall. However, both measures are noisy, so it can help farmers to use both measures. Additionally, if there are costs associated with switching from one crop to another (e.g. learning costs or investment costs), then farmers might want to use predictions based on decade lagged rainfall, since this gives predictions of what rainfall will be, on average, over the next several years.

if recent years of rainfall have been above average. Finding these results would indicate that farmers are adapting their crop portfolio in response to the variations in the monsoon regimes.

5.4 Rainfall Specifications

For the regressions where I test for adaptation via irrigation investment or crop choice, I use two different specifications of lagged decade rainfall. Let $rain_{jt}$ be the deviation of current year rainfall from its historical mean for the village, expressed as a z-score. In Specification 1, I simply use mean rainfall over the past decade, e.g.

$$\frac{1}{10}\sum_{k=1}^{10} L^k(rain_{jt})$$

In Specification 2, I use the prevalence of especially wet or especially dry years over past decade. In particular, in the regression I control for both

$$\frac{1}{10}\sum_{k=1}^{10} L^k(\mathbf{1}\{rain_{jt}\text{in lowest quintile}\})$$

and

$$\frac{1}{10}\sum_{k=1}^{10} L^k(\mathbf{1}\{rain_{jt}\text{ in highest quintile}\})$$

The idea with the second specification is that especially wet or especially dry years may be more salient to farmers, and that they may respond more to these especially wet or dry shocks than they do the mean decade rainfall. Additionally, these specifications may have more econometric power to identify an effect, than the specifications using mean lagged rainfall.

6 Results

6.1 Return to Irrigation

The results of the regression for the return to irrigation are given in Table 4. The first two columns give the results for the REDS dataset and the dependent variable is profits per acre. Note that column 1 deducts the value of family labor as equal to the market wage, and column 2 does not deduct family labor (e.g. sets its shadow value equal to zero). As can be seen from the table, higher rainfall is good for profits. In particular, the coefficient on indicator for ”rainfall above the 80th percentile” is positive. The coefficient on proportion land irrigated is positive, indicating that irrigation increases profits in a level sense. However, the interaction between proportion land irrigated and ”rainfall above the 80th percentile” is negative, indicating that the return to irrigation is higher during dry years than it is during wet years. Hence, both of the assumptions outlined in Section 3.2 are borne out by the data.

The results of the regression for the return to irrigation for the WB data set are given in column 3 of Table 4. Similarly to the household data set, it can be seen from the table that crop yields are higher during wet years than they are during dry years, and that the return to irrigation is higher during dry years than it is during wet years.

6.2 Testing for Adaptation via Irrigation Investment

Table 5 presents the results of the regressions that test whether farmers adapt their irrigation investment in response to the rainfall regimes. The first four columns use the REDS data and the dependent variable is an indicator for whether the household invested in irrigation during the recall period of the survey. In column 1, I regress the proportion of land irrigated on lagged mean rainfall from the past decade, *without* including a control for wealth. The coefficient on lagged rainfall is negative which supports an adaptation story: farmers are investing more in irrigation after decades that have been especially dry. In column 2, I control for non-land wealth and instrument for it with inherited non-land wealth. The coefficient on lagged rainfall remains negative, which also supports an adaptation story.

In columns 3 and 4, I repeat the same specification but use a different measure of lagged rainfall: the proportion of years in the past decade that were above the 80th percentile for rain, and the proportion that were below the 20th percentile. Again, I find evidence of an adaptation effect: farmers invest less in irrigation if there have been a lot of especially wet years in the past decade.

Using the standard deviation of the lagged rainfall variables presented in Table 2, along with the estimated response coefficient from column 1, I find that farmers increase their probability of investing in irrigation by 1.9 percentage points, for a one standard-deviation change in the lagged rainfall variable. Since the average probability of investing in irrigation during the recall period is 5%, this is a substantial effect.

Columns 5 and 6 of Table 5 test for adaptation via irrigation, using the WB district-level data set. Here the dependent variable is the one-year change in irrigated area at the district level. Similarly to the household-level data set, investment in irrigation is higher after decades that have been particularly dry, which supports an adaptation story in which farmers are updating their expectations over future weather, based on past rainfall shocks.

6.3 Testing for Adaptation via Crop Choice

Table 6 presents the results of the regressions that test whether farmers adapt their crop portfolio in response to the rainfall regimes. In all columns, I use the specification where I measure lagged rainfall based on the proportion of wet and dry shocks (e.g. years above the 80th percentile or below the 20th percentile) in the past decade. The first three columns of the table use the REDS data. In the first column, we see that, conditional on wealth, having more wet shocks and having less dry shocks leads to higher water needs of the crops, which is consistent with an adaptation effect. In the second column, I test how the proportion of area planted to drought-tolerant crops responds to lagged rainfall from the past decade. I find that farmers plant less area to drought-tolerant crops following a decade with lots of especially wet shocks, which is consistent with an adaptation effect. Lastly, in column 3 I explore how lagged rainfall affects the proportion of area planted to highly drought sensitive crops. I find that the area of drought-sensitive crops goes down if there have been a lot of very dry (below the 20th percentile) years in the past decade for that village. Appendix Table 8 replicates the same specification as Table 6, but uses mean rainfall from the past decade, instead of the wet and dry shock specification.

In columns 4-6 of Table 6, I present the results of the test for adaptation via crop choice with the World Bank dataset. The results for crop water need (column 4) and area planted to drought tolerant crops (column 5) follow the same patterns as the results for the REDS data, and are consistent with an adaptation story. However, since I don't have a control for wealth in the WB specification, it is possible that these effects are driven by a wealth effect. However, in column 6 I get the unexpected results that farmers plant *more* area to drought-sensitive crops after a decade with lots of dry shocks. This result is consistent with neither an adaptation effect, nor with a wealth effect. When I look at each drought-sensitive crop individually, I get that the result is driven by rice (table not shown). I am still looking into what could be driving this unexpected effect.

7 Extensions

In this section, I extend my results in two directions. First, I estimate the extent to which farmers are able to protect their profits from harmful variations in the climate, based on climate variations in my historical sample. Secondly, I use my estimates of adaptation to historical variations in the climate to construct projections for future adaptation to climate change, under a counterfactual scenario in which there are changes in future precipitation, but no changes in future temperature.

7.1 Impact of Adaptation on Profits

I estimate the impact of adaptation on profits, for the period 1971-1999, using the REDS data. Recall that, during this period, rainfall for most of India was below its historical mean. I am interested in calculating how much lower profits were, due to the deficient rainfall during this period. I am also interested in calculating what fraction of lost profits farmers were able to recover, via adaptation.

I am not able to calculate the impact of crop choice adaptation on profits, because I do not have an unbiased estimate of the impact of crop choice on profits.[18] However, I am able to calculate the impact of irrigation adaptation on profits. I use the estimated coefficients from Table 4, column 2 to get the return to irrigation. To calculate the adaptive response to lagged rainfall, I use the coefficients from a specification similar to my main irrigation adaptation table (e.g. Table 5), except that the dependent variable is the proportion of land irrigated, instead of being an indicator for whether the household invested in irrigation during the recall period (table not reported).[19]

In Figure 7, I compare for each household what the total profits were for the period 1971-1999, compared to what the expected profits would have been had the climate been at its historical mean distribution. I find that the net effect across all households was to decrease profits by 0.4%. However, there is substantial heterogeneity amongst the impact on profits, and for households with negative impacts (e.g. households whose rainfall was below its historical mean for most of the period), the average loss was 2.8%. I then calculate what profits would have been for each household under the realized climate, but if the farmers had not adapted their irrigation input. Comparing these counterfactual prof-

[18]Specifically, area planted to drought-tolerant rips is a choice variable, and I don't have an appropriate instrument for it. Unobserved shocks, such as health shocks, may be correlated with both profits and with drought-tolerant area, and hence a regression of profits on drought-tolerant area will be biased.

[19]I use this alternative specification because in the data I don't know what fraction of the farmer's land becomes irrigated when then invest in irrigation, so I need to use the alternative specification to calculate the impact of adaptation on profits, since profits depend on proportion of land irrigated.

its to the actual profits, I find that farmers were only able to recover 15% of the profits that they lost due to the drier climate. Hence, the majority of lost profits were not recovered via adaptation.

Note that Guiteras (2009) predicts that crop yields in India will be 4.5 to 9% lower in the medium run (2010-2039) due to anthropogenic climate change. His estimates are an upper bound, since he employs the panel approach, which assumes zero adaptation. However, if we extrapolate my results on adaptation, and specifically assume that farmers will recover 15% of total losses, then the actual impact on crop yields, inclusive of adaptation, will be more like 3.8 to 7.7%, which is still substantial.

7.2 Adaptation Projections for a Counterfactual Climate Change Scenario

I now use the estimates of adaptation to historical variations in the climate to construct projections for future adaptation to climate change, under a counterfactual climate change scenario of an increase in precipitation, but no increase in temperature. Before presenting the projections, I will discuss one strength of my projections, followed by several important caveats. In the medium-run (2012-2039), India's mean summer temperature is expected to increase by 0.5°C, and India's summer rainfall is expected to increase by 4%, according to the business-as-usual scenario from the IPCC 4th assessment report (Christensen and Hewitson, 2007). One strength of my projections is that the projected increase in precipitation is very similar to the magnitude of precipitation changes under the monsoon rainfall regimes. Hence, I don't have to worry about making predictions based on very different magnitudes of rainfall change.

However, there are several important caveats to consider. The most important caveat is that I don't have any projections for adaptation to temperature, since there is no statistically significant variation in temperature across the monsoon regimes. A second caveat is that there is uncertainty over the climate change predictions, especially precipitation. Different models have different predictions for India's future precipitation. Therefore, the actual change in precipitation over the next thirty years may be greater or less than 4%. A third caveat is that in addition to the 4% increase in mean summer precipitation, it is also possible that there will be increases in year-to-year variability of rainfall, as well as potential changes to intra-seasonal patterns of precipitation (e.g. break periods in the monsoon). These changes could have impacts on farmers irrigation and crop choice decisions. A fourth caveat is that adaptation to a future precipitation *trend* may be different than adaptation to historical rainfall *regimes*. A fifth caveat is that there are trends in covariates, such as income, wealth, land size and technology, all of which impact irrigation and crop choice decisions, and none of which I am controlling for. A sixth and final caveat is under anthropogenic climate change there are likely to be price effects which will diminish the magnitude of adaptation that occurs. This will in particular be true if the changes in precipitation under anthropogenic climate change exhibit less spatial variation than the changes of precipitation under the monsoon rainfall regimes.

In sum, the projections I am about to present should not be thought of as accurate predictions of the future, but rather as limited projections of how adaptation to new precipitation levels may impact future irrigation and crop choice decisions. With these caveats in mind, I present Table 7, which shows the outcome variables of proportion land irrigated, average water need of crop portfolios, and proportion of area planted to drought-tolerant and drought-sensitive crops. In the first column, I present the values of these outcome variables for the year 1999, based on the REDS household data, using the household weight that make the data set nationally representative. In column 2, I present projections for the outcome variables for 2039, under a scenario of no adaptation. Since there is no evidence of a trend for the crop choice variables, for those three variables the values are the same as the 1999 values. However, proportion of land irrigated indicates a clear linear increasing trend in the household dataset, so I include that trend: specifically I project that proportion of land irrigated will increase from 0.483 to 0.645 (absent any adaptation). Column 3 shows the projections for the outcome variables, allowing for adaptation, and using the adaptation response estimated from the REDS data.[20] Column 4 reports the change in each outcome variable due to adaptation. I project that the proportion of land irrigated will decrease 11 percentage points, relative to its increasing historical trend. I project that the average water need of crop portfolio will decrease by 51 millimeters. I project that the proportion of area planted to drought tolerant crops will decrease by 16 percentage points and the proportion planted to drought-sensitive crops will increase by 15 percentage points.

8 Conclusion

In this paper, I have argued that we can use historical variation in the India monsoon to test whether farmers have been adapting to medium-run changes in their climate. The Indian monsoon undergoes zonal and meridional regimes, in which droughts or floods

[20] In Table 5, I estimate the adaptation response using the dependent variable that is an indicator for whether the household invested in irrigation during the recall period. For the projections, I am interested in the stock of irrigated land, so I use an alternative specification (not reported) where the dependent variable is the proportion of land irrigated.

are more common respectively, and these regimes last several decades. I find evidence that farmers adjust their irrigation investment and the water-intensiveness of their crop portfolio depending on which monsoon regime they currently face. Specifically, for a one standard deviation decrease of the lagged mean rainfall variable, farmers increase their probability of investing in irrigation by 1.9 percentage points and increase the area planted to drought-tolerant crops by 2.1 percentage points. However, I find that adaptation only enables farmers to recover 14% of the profits that they have lost due to harmful changes in their climate.

In sum, I find that farmer do indeed adapt to changes in their climate, but that there ability to protect their agricultural profits via adaptation appears to be very limited. This suggests that there may be substantial financial and informational barriers to adaptation. In the case of irrigation investment, credit constraints clearly may inhibit optimal investment and adaptation. And in the case of crop choice, lack of knowledge about different crop types may inhibit adaptation. Future work needs to be done in order to address the issues of what institutions, infrastructures, technologies and policies best support adaptation. Future work should also explore in more detail what the various financial and informational barriers to adaptation are. Lastly, future work should explore how adaptive capacity varies across different sub-populations.

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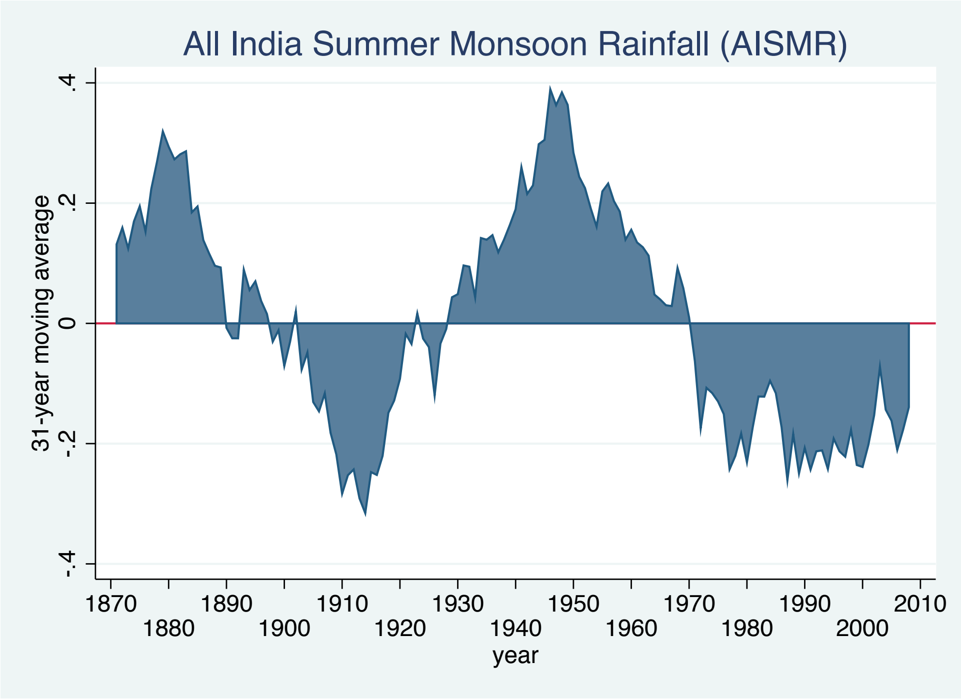
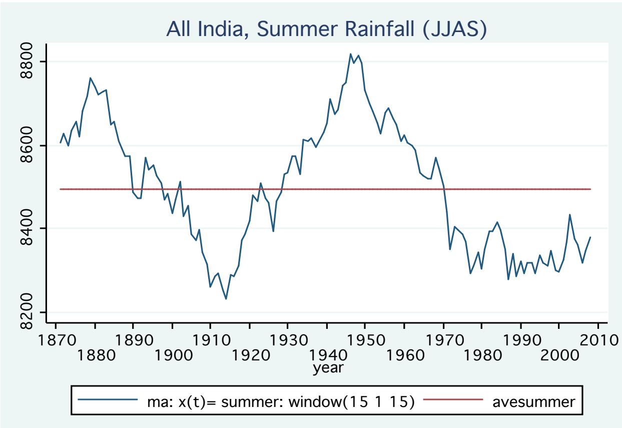
Figure 1: Moving Average of the Indian Monsoon





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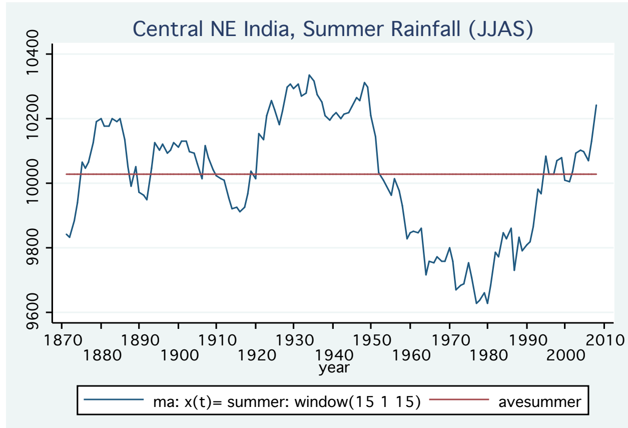

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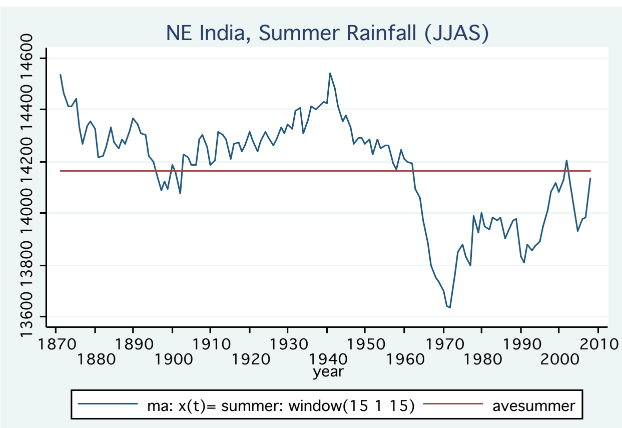

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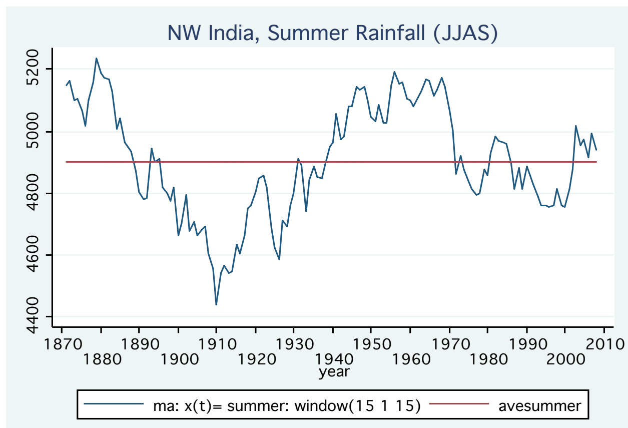

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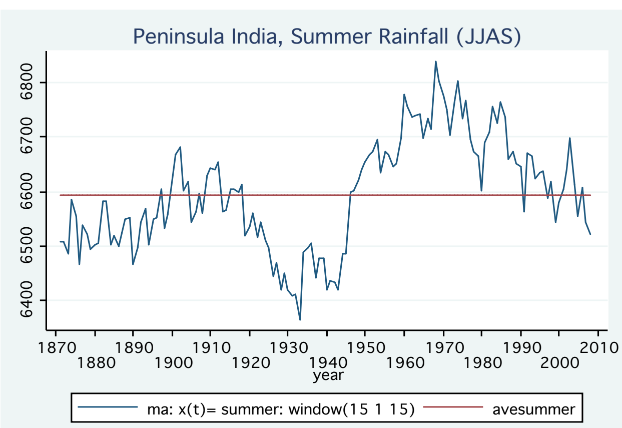

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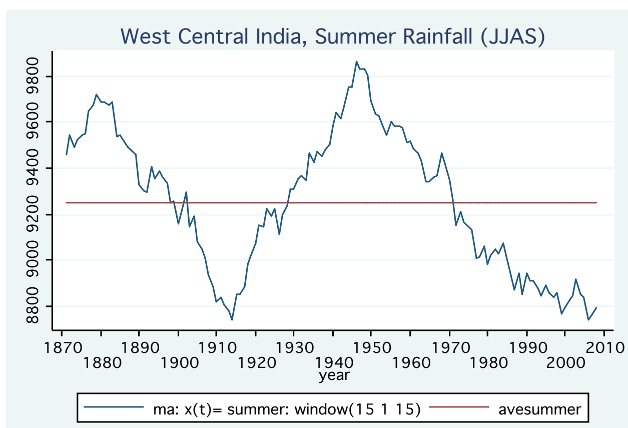

(f)

Figure 2: 31-year moving average of summer rainfall, for all-India and for the five meteorological regions

Figure 3: All India Summer Monsoon (AISMR)

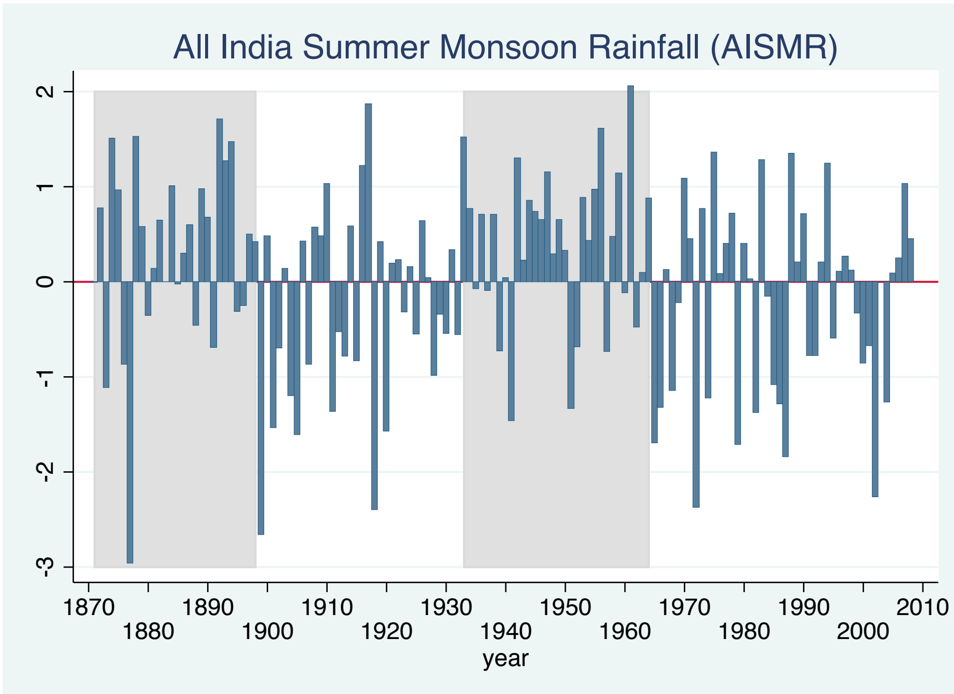

Figure 4: Histogram

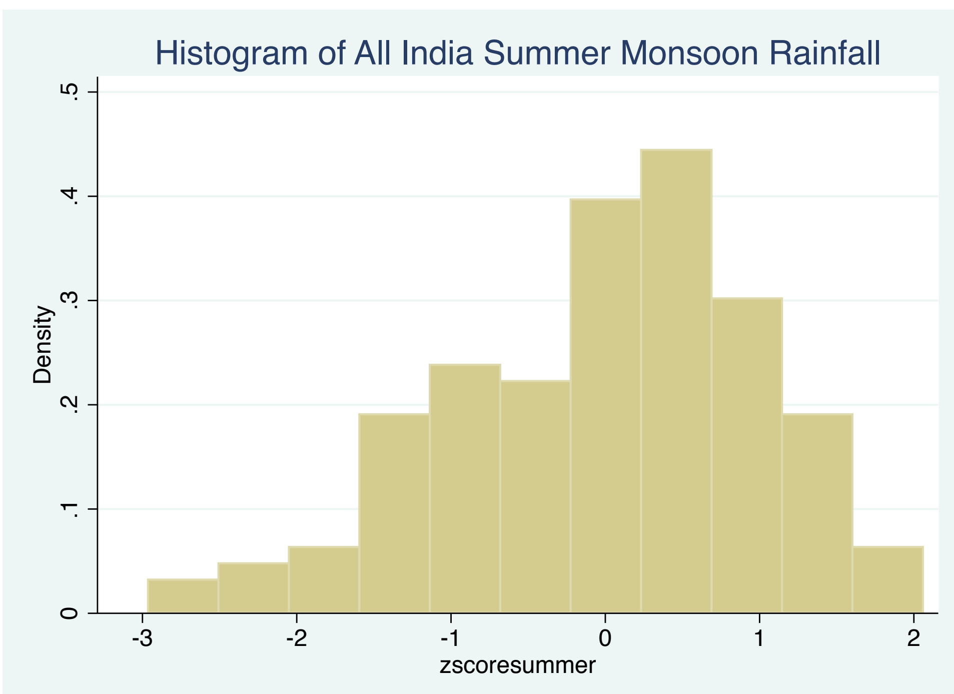

Figure 5: Histogram

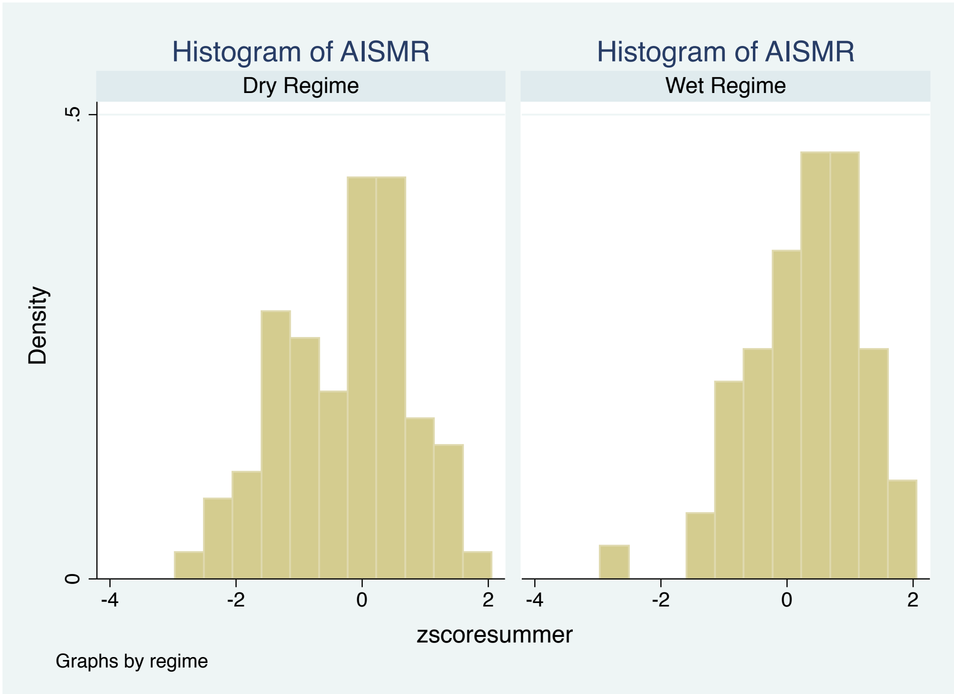

Figure 6: Moving Average of Temperature

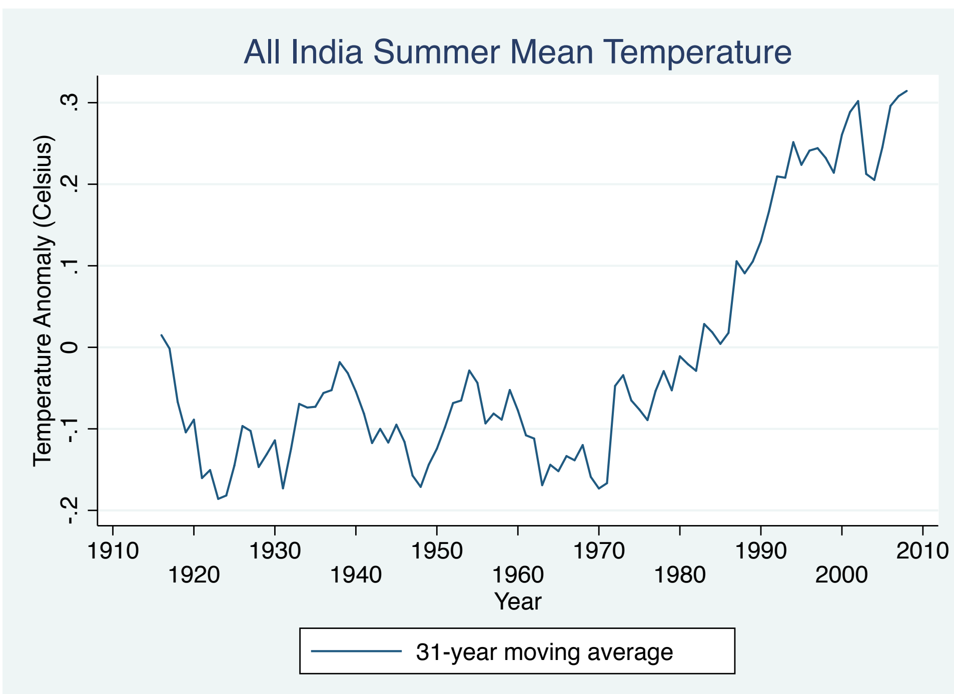

Figure 7: Fraction of Profits Gained or Lost Due to Climate Variation (1971-1999)

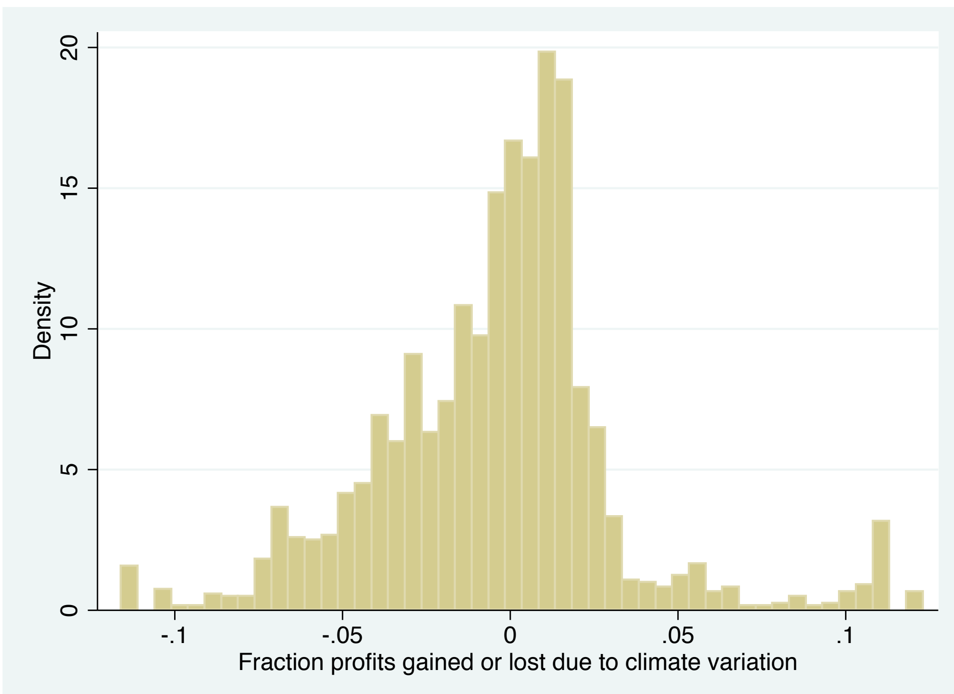

Table 1: Crop Water Needs and Sensitivity to Drought

Crop	Crop water need (mm/total growing period)	Sensitivity to drought
Barley	450-650	low-medium
Cotton	700-1300	low
Maize	500-800	medium-high
Millet	450-650	low
Peanut	500-700	low-medium
Potato	500-700	high
Pulses	350-500	medium-high
Rice	450-700	high
Sorghum	450-650	low
Soybean	450-700	low-medium
Sugarcane	1500-2500	high
Sunflower	600-1000	low-medium
Wheat	450-650	low-medium

Source: Brouwer and Heibloem (1986)

Table 2: [REDS] Summary Statistics

	1971	1982	1999
Profits per acre (1971 Rs.)	502.96	586.6	741.7
	(440.9)	(654.9)	(940.0)
Profits per acre, deducting family labor (1971 Rs.)	-	375.3	425.3
		(530.9)	(819.2)
Proportion land irrigated	0.378	0.414	0.483
	(0.437)	(0.455)	(0.466)
Irrigation investment during RP (dummy)	0.0767	0.0724	0.0116
	(0.266)	(0.259)	(0.107)
Nonland wealth (1971 Rs.)	5591.6	2656.9	18217.9
	(7287.2)	(5717.8)	(28808.6)
Average water need of crop portfolio	-	576.4	583.8
		(67.69)	(82.86)
Proportion area planted to drought-tolerant crops	-	0.264	0.166
		(0.340)	(0.314)
Proportion area planted to drought-sensitive crops	-	0.392	0.476
		(0.391)	(0.395)
Current year rain	0.313	0.208	0.279
	(0.929)	(0.772)	(0.723)
10-yr lagged average rain	-0.000634	0.0653	-0.0303
	(0.328)	(0.251)	(0.326)
10-yr lagged average of dry shock	0.196	0.183	0.166
	(0.125)	(0.0925)	(0.150)
10-yr lagged average of wet shock	0.177	0.220	0.167
	(0.122)	(0.130)	(0.124)

mean coefficients; sd in parentheses
Cultivating households only.

Table 3: [WB] Summary Statistics

	1956	1971	1986
Weighted log crop yield	-0.285	-0.0204	0.190
	(0.331)	(0.342)	(0.397)
Proportion of land irrigated	0.178	0.234	0.321
	(0.175)	(0.203)	(0.256)
Average water need of crop portfolio	563.4	568.9	576.3
	(51.58)	(51.24)	(49.55)
Proportion area planted to drought-tolerant crops	0.257	0.240	0.227
	(0.265)	(0.262)	(0.263)
Proportion area planted to drought-sensitive crops	0.315	0.321	0.344
	(0.318)	(0.314)	(0.309)
Current year rain	0.579	0.436	-0.400
	(0.883)	(1.007)	(0.748)
10-yr lagged average rain	0.108	0.000608	-0.0353
	(0.294)	(0.288)	(0.234)
10-yr lagged average of dry shock	0.176	0.203	0.191
	(0.111)	(0.122)	(0.106)
10-yr lagged average of wet shock	0.224	0.185	0.163
	(0.133)	(0.106)	(0.115)

mean coefficients; sd in parentheses

Table 4: Impact of Irrigation and Rainfall on Profits

Data set:	REDS	REDS	WB
Specification:	FE-IV	FE-IV	FE
Dependent variable:	profit (fam. labor)	profit	log yield
	(1)	(2)	(3)
Rain below 20th percentile	12.77	-42.34	-0.180***
	(139.8)	(149.1)	(0.0168)
Rain between 20th and 40th percentiles	71.57	67.21	-0.0474***
	(85.75)	(93.56)	(0.0112)
Rain between 60th and 80th percentiles	132.9*	71.06	0.00379
	(76.91)	(82.66)	(0.00939)
Rain above 80th percentile	312.0***	332.8***	-0.0188*
	(70.96)	(74.40)	(0.0104)
Proportion of land irrigated	372.1***	441.7***	0.573***
	(115.3)	(129.8)	(0.0687)
Propirr*Rain below 20th percentile	-169.5	-84.43	0.265***
	(161.0)	(174.7)	(0.0403)
Propirr*Rain between 20th and 40th	-200.8	-137.1	0.0929***
	(142.6)	(153.2)	(0.0292)
Propirr*Rain between 60th and 80th	-126.9	-57.40	-0.000540
	(123.5)	(132.1)	(0.0252)
Propirr*Rain above 80th percentile	-416.8**	-426.9**	0.0160
	(174.0)	(204.4)	(0.0289)
Temperature	6.659	-10.16	-0.0215***
	(33.04)	(39.48)	(0.00416)
Nonland wealth (1971 Rs) / 10^6	2765.5**	1871.6	
	(1103.7)	(1168.1)	
Fixed effects	Farmer	Farmer	District
Year fixed effects	Yes	Yes	Yes
Observations	6827	6827	8384

Standard errors in parentheses
Growing season rainfall. Village level clustering (REDS); district level clustering (WB).
Years 1982 and 1999 (REDS); years 1956-1986 (WB).
Proportion land irrigated instrumented with proportion inherited land irrigated (REDS only).
Non-land wealth instrumented with inherited non-land wealth (REDS only).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 5: Testing for Adapation via Irrigation Investment

Data set:	REDS	REDS	REDS	REDS	WB	WB
Specification:	FE	FE-IV	FE	FE-IV	FE	FE
Dependent variable:	irrig. inv.	irrig. inv.	irrig. inv.	irrig. inv.	irrig. ch.	irrig. ch.
	(1)	(2)	(3)	(4)	(5)	(6)
Proportion of land irrigated	0.0751***	0.0949***	0.0767***	0.0966***	46.18***	46.03***
	(0.0186)	(0.0256)	(0.0184)	(0.0255)	(3.875)	(3.853)
1-yr lagged rain	-0.00505	-0.0146*	-0.00451	-0.0143	-0.305	-0.349
	(0.00708)	(0.00865)	(0.00699)	(0.00895)	(0.231)	(0.230)
Nonland wealth (1971 Rs) / 10^6		-0.434		-0.425		
		(0.524)		(0.524)		
10-yr lagged average rain	-0.0626**	-0.0975**			-1.491**	
	(0.0261)	(0.0407)			(0.594)	
10-yr lagged average of dry shock			0.167**	0.221**		3.252**
			(0.0702)	(0.0977)		(1.605)
10-yr lagged average of wet shock			-0.0637	-0.0867		-0.595
			(0.0649)	(0.0844)		(1.430)
Fixed effects	Farmer	Farmer	Farmer	Farmer	District	District
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	9204	6827	9204	6827	8113	8113

Standard errors in parentheses

Growing season rainfall. Village level clustering (REDS); district level clustering (WB).

Col 1,3: Years 1971, 1982, 1999. Col 2,4: Years 1982, 1999. Years 1956-1986 (WB).

Proportion land irrigated instrumented with proportion inherited land irrigated (REDS only, Cols 2 and 4).

Non-land wealth instrumented with inherited non-land wealth (REDS only).

Dry shock is rain below 20th percentile; wet shock is rain above 80th percentile.

Dependent variable is an indicator for investing in irrigation during the recall period (REDS).

Dependent variable is the one-year change in irrigated area (WB).

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 6: Testing for Adapation via Crop Choice

Data set:	REDS	REDS	REDS	WB	WB	WB
Specification:	FE-IV	FE-IV	FE-IV	FE	FE	FE
Dependent variable:	water need	tolerant	sensitive	water need	tolerant	sensitive
	(1)	(2)	(3)	(4)	(5)	(6)
Proportion of land irrigated	-2.577	-0.100***	0.0306	47.67***	-0.0522***	0.160***
	(9.505)	(0.0265)	(0.0287)	(6.463)	(0.0149)	(0.0241)
Current year rain	0.194	0.0100	0.00956	-0.682***	-0.00362***	0.00100*
	(2.942)	(0.0126)	(0.0109)	(0.183)	(0.000597)	(0.000600)
Nonland wealth (1971 Rs) / 10^6	-275.0***	0.161	-0.699*			
	(89.98)	(0.317)	(0.364)			
10-yr lagged average of dry shock	-36.88*	-0.148	-0.203***	4.626	0.00523	0.0300**
	(19.47)	(0.0980)	(0.0702)	(3.585)	(0.00920)	(0.0119)
10-yr lagged average of wet shock	54.63**	-0.175**	0.0292	7.253*	-0.0180*	0.00623
	(21.35)	(0.0808)	(0.0574)	(3.695)	(0.00966)	(0.0123)
Fixed effects	Farmer	Farmer	Farmer	District	District	District
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5408	5467	5467	8384	8384	8384

Standard errors in parentheses

Growing season rainfall. Village level clustering (REDS); district level clustering (WB).

Years 1982 and 1999 (REDS). Years 1956-1986 (WB).

Proportion land irrigated instrumented with proportion inherited land irrigated (REDS only).

Non-land wealth instrumented with inherited non-land wealth (REDS only).

Dry shock is rain below 20th percentile; wet shock is rain above 80th percentile.

Dependent variable is average crop water need, or proportion area planted to drought-tolerant or drought-sensitive crops.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 7: Projections for Adaptation for a Counterfactual Climate Change Scenario (Precipitation Change Only)

Outcome	1999	2039 projection, no adaptation	2039 projection, with adaptation	Change due to adaptation
Prop. irrigated	0.483	0.645	0.528 (0.416, 0.640)	-0.117 (-0.229, -0.005)
Ave. water need	583.8	583.8	634.9 (595.7, 674.0)	51.06 (11.94, 90.18)
Prop. tolerant	0.166	0.166	0.003 (0.000, 0.151)	-0.163 (-0.310, -0.015)
Prop. sensitive	0.476	0.476	0.623 (0.523, 0.722)	0.147 (0.047, 0.246)

95% confidence intervals in parenthesis

Table 8: Appendix Table: Same as Table 6 But with Different Rainfall Specification

Data set:	REDS	REDS	REDS	WB	WB	WB
Specification:	FE-IV	FE-IV	FE-IV	FE	FE	FE
Dependent variable:	water need	tolerant	sensitive	water need	tolerant	sensitive
	(1)	(2)	(3)	(4)	(5)	(6)
Proportion of land irrigated	-2.928	-0.0971***	0.0314	48.04***	-0.0523***	0.163***
	(9.841)	(0.0269)	(0.0282)	(6.429)	(0.0150)	(0.0243)
Current year rain	-0.317	0.0107	0.00900	-0.672***	-0.00375***	0.00107*
	(2.902)	(0.0131)	(0.0112)	(0.189)	(0.000604)	(0.000620)
Nonland wealth (1971 Rs) / 10^6	-288.0***	0.410	-0.545			
	(94.09)	(0.334)	(0.378)			
10-yr lagged average rain	22.22**	-0.0420	0.0265	0.518	-0.0103***	-0.00528
	(9.570)	(0.0340)	(0.0268)	(1.353)	(0.00375)	(0.00432)
Fixed effects	Farmer	Farmer	Farmer	District	District	District
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Observations	5408	5467	5467	8384	8384	8384

Standard errors in parentheses

Growing season rainfall. Village level clustering (REDS); district level clustering (WB).

Years 1982 and 1999 (REDS). Years 1956-1986 (WB).

Proportion land irrigated instrumented with proportion inherited land irrigated (REDS only).

Non-land wealth instrumented with inherited non-land wealth (REDS only).

Dry shock is rain below 20th percentile; wet shock is rain above 80th percentile.

Dependent variable is average crop water need, or proportion area planted to drought-tolerant or drought-sensitive crops.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$