Adaptation to Climate Change: Historical Evidence from the Indian Monsoon

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July 23, 2015

Abstract

Estimating the potential impacts of climate change requires understanding the ability of agents to adapt to changes in their climate. This paper uses panel data from India spanning 1956–1999 to investigate the ability of farmers to adapt. To identify adaptation, I exploit persistent, multidecadal monsoon regimes, during which droughts or floods are more common. These regimes generate medium-run variation in average rainfall, and there is spatial variation in the timing of the regimes. Using a fixed effects strategy, I test whether farmers have adapted to the medium-run rainfall variation induced by the monsoon regimes. I find solid evidence that farmers adjust their irrigation investments and more limited evidence of crop adaptation. However, adaptation only recovers 13% of the profits farmers have lost due to adverse climate variation.

1 Introduction

Climate scientists broadly agree that the global climate is changing and that these changes will accelerate in coming decades (Christensen and Hewitson, 2007). However, estimates of the economic

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impacts of climate change vary widely, in large part due to uncertainty about adaptation (Mendelsohn et al., 1994; Adams et al., 1998; Schlenker et al., 2005; Deschênes et al., 2007; Schlenker and Roberts, 2009; Tol, 2014). Rapid adaptation may curb economic damages, but slower adaptation will likely magnify them. Understanding adaptation is particularly crucial in developing countries and in the agricultural sector, as both are especially vulnerable to climate change (Parry, 2007).

Recent scholarship has typically estimated climate change damages using year-to-year weather variation to compare economic outcomes under hotter versus cooler temperatures. This climate–economy relationship is then extrapolated to future climate change to estimate impacts (Deschênes et al., 2007; Schlenker and Roberts, 2009; Guiteras, 2009; Dell et al., 2012; Burgess et al., 2014).\(^1\) Since these calculations rely on annual weather variability, they do not account for possible adaptations that agents may undertake in response to sustained climate change. Therefore, to assess the accuracy of these estimates, it is vital to predict the likely extent of future adaptation.

In this paper, I exploit historical rainfall variation in India to estimate adaptation. Rather than analyzing year-to-year weather deviations, I focus on climate fluctuations that last several decades. The Indian monsoon undergoes multidecadal phases during which droughts or floods are more common. These monsoon phases induce persistent deviations in rainfall from decade to decade. I test whether farmers adapt their irrigation investments and crop portfolios in response to these persistent rainfall deviations.\(^2\)

Figure 1 shows a moving average of India’s summer rainfall, highlighting the monsoon phases. These phases induce persistent rainfall deviations and, hence, lagged rainfall provides information about future rainfall. Therefore, forward-looking farmers should adjust their agricultural decisions in response to recent weather.

I test for adaptation by analyzing whether agricultural decisions respond to lagged weather, looking specifically at irrigation investments and drought-tolerant crop areas. I exploit the fact that the return to irrigation investment varies across wet versus dry growing seasons and that, similarly,\(^1\) Another methodology uses cross-sectional climate variation to link climate and the economy, but this work suffers from potential omitted variable bias (Mendelsohn et al., 1994; Schlenker et al., 2005; Sanghi and Mendelsohn, 2008).\(^2\) The monsoon regimes don’t cause variation in temperature, so I do not analyze adaptation to temperature changes.
the relative yields of different crops vary across wet versus dry growing seasons. My empirical strategy is to regress irrigation assets and crop portfolios on rainfall from the past decade, while controlling for current rainfall, wealth, household fixed effects, and year fixed effects. Regional variation in the timing of the monsoons, displayed in Figure 2, allows me to include year fixed effects in my regressions and, hence, I can separate adaptation to rainfall from unrelated temporal changes in irrigation and crop choice.

Analyzing two agricultural data sets, I find strong evidence of irrigation adaptation and limited evidence of crop adaptation. Each additional dry year in the past decade increases the probability that a farmer will invest in irrigation by 1.7 percentage points, relative to a baseline 5% probability of investing. Each additional dry year in the past decade decreases the area that a farmer plants with drought-sensitive crops by 1.9 percentage points. The baseline proportion of crop area planted with drought-sensitive crops is 37%. In addition to testing for the presence of adaptation, I also measure the extent to which adaptation prevents profit losses. I find that farmers are able to recover only a limited amount of their lost profits by adapting. Specifically, in the face of sustained adverse weather conditions, adaptation recovers only 13% of lost profits.

Significantly, this study only analyzes irrigation and crop choice. Data limitations do not permit me to study other potential adaptations, such as adjusting fertilizer and agricultural inputs (Duflo et al., 2011), shifting sowing dates (Giné et al., 2009), purchasing crop insurance (Di Falco et al., 2014), switching out of agriculture (Rose, 2001), or migrating (Viswanathan and Kavi Kumar, 2015). Additionally, since the monsoon regimes affect only precipitation, I do not analyze adaptation to temperature changes.

This paper contributes to a rapidly growing literature on climate change adaptation. Researchers have used a variety of techniques to identify the magnitude and efficacy of adaptation, including extrapolating from cross-sectional climate variation (Seo et al., 2010; Kurukulasuriya et al., 2011; da Cunha et al., 2014), measuring long-run responses to one-time environmental

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3The drought-tolerant crops analyzed have lower expected yields, which is why farmers do not plant them exclusively.
4Dell et al. (2014) present a helpful synthesis of this literature.
shocks (Hornbeck, 2012; Deryugina, 2013; Hornbeck and Naidu, 2015), implementing instrumental variables approaches to address the endogeneity of adaptation (Di Falco and Veronesi, 2013, 2014), studying whether new technologies have changed weather impacts over time (Barreca et al., 2015), analyzing differential weather impacts by the long-run frequency of the event (Deschênes and Greenstone, 2011; Hsiang and Narita, 2012), and, lastly, using a “long-difference” approach that compares short-run weather impacts with long-run impacts (Dell et al., 2012; Burke and Emerick, 2015).

The current study resembles the long-difference approach more than any other. The long-difference approach uses spatial variation in recent warming trends to test for medium-run adaptation. By comparing the impacts of short-run weather fluctuations to the impacts of medium-run warming trends, the researchers can measure the magnitude of adaptation. Dell et al. (2012) look at the impact of temperature shocks on cross-country economic growth, and find little difference between short-run and medium-run impacts, suggesting limited adaptation over this time frame. Burke and Emerick (2015) analyze US agricultural yields for corn and soy and find that twenty years of potential adaptation have reduced less than half, and in some cases none, of the short-term negative impacts of higher temperatures. Like these papers, I also exploit spatial variation of medium-run changes in climate. As in the long-difference research, using changes in climate over time (rather than cross-sectional climate variation) allows me to control for farmer-specific unobservables that may be correlated with both adaptation decisions and agricultural yields.

Relative to existing work that uses the long-difference strategy, this paper makes two novel contributions. First, I analyze agriculture in the context of a developing country. Since predictions suggest climate change will harm developing country farmers more than others, this is an important context to analyze. Second, I analyze how farmers adapt two specific outcomes (irrigation and crop choice) to changes in medium-run climate. Previous long-difference work, in contrast, has analyzed the response of yields (or economic growth) to medium-run climate, which allows one to infer the total extent of adaptation but does not give insight into the specific channels of adaptation.

\footnote{Typically, this literature defines the “medium-run” as roughly a ten- to twenty-year time frame.}
These two approaches are complementary, since it is desirable to know both the total impacts of adaptation, as well as the specific adaptations that farmers are undertaking. More broadly, I contribute to an expanding literature on agricultural adaptation in India (Mendelsohn, 2008; Sanghi and Mendelsohn, 2008; Khan et al., 2009; Fishman, 2012).

The paper is organized as follows. Section 2 describes the monsoon phases in greater detail. Section 3 presents a model of climate, irrigation, and crop choice. Section 4 describes the data, and Section 5 proposes the empirical strategy. Section 6 presents the main results. In Section 7, I discuss several robustness tests that I perform in a separate, supplementary file. Section 8 calculates the fraction of lost profits farmers recovered by adapting. Section 9 concludes.

2 Background on Interdecadal Rainfall Variability

Indian agriculture depends heavily on the summer monsoon, which occurs during June, July, August, and September (Krishna Kumar et al., 2004). Because India’s climate is semi-arid, wetter monsoons increase agricultural output, and drier monsoons decrease it (Das, 1995; Jayachandran, 2006). Monsoon rainfall exhibits high interannual variability, as shown in Figure 3. The monsoon also undergoes interdecadal variability, in the form of wet and dry phases that typically each last for about three decades (Pant and Kumar, 1997). Meteorologists refer to these as meditional and zonal regimes, respectively. Figure 3 shades the wet regimes gray; Figure 1 smoothes annual rainfall with a moving average filter, to further highlight the regimes.

The monsoon regimes cause average rainfall to vary more from decade to decade than it would if rainfall was independent and identically distributed (i.i.d.). This persistent decadal variation means that lagged rainfall has predictive value for future rainfall. If rainfall was i.i.d., then lagged

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6Meteorologists widely agree upon the existence of the monsoon regimes (Subbaramayya and Naidu, 1992; Kripalani and Kulkarni, 1997; Pant and Kumar, 1997; Pant, 2003; Varikoden and Babu, 2014). The precise mechanisms that generate the regimes are not well understood, in part due to a lack of good quality data for a sufficiently long period. One theory is that an atmospheric-oceanic feedback mechanism induces the regimes (Wang, 2006).

7Mooley and Parthasarathy (1984) and Kripalani and Kulkarni (1997) perform statistical analysis demonstrating that the monsoon regimes are statistically significant. That is, they demonstrate that the interdecadal rainfall variability is greater than what we would expect under an i.i.d process. In Section B of the supplementary file, I describe their analysis in greater detail and also run an additional test that further verifies the monsoon’s non-stationarity.
rainfall would not have this predictive element. Rational farmers should notice these persistent rainfall variations and update their future rainfall expectation in response. This updating could occur even if farmers were not aware of the existence of the monsoon regimes, per se. On the other hand, if rainfall were i.i.d., lagged rainfall would have no predictive value and it would be irrational for farmers to update their rainfall expectations in response to it. The statistical significance of the decadal variations allows me to interpret a farmer’s response to lagged rainfall as evidence of rational adaptation, rather than an indicator of irrational behavior.

The monsoon regimes are not geographically homogeneous. There is significant spatial variation in the length and timing of the regimes (Subbaramayya and Naidu, 1992). In particular, rainfall in the southern peninsula and the easternmost region tends to be out of phase with the rest of the country (Wang, 2006). Figure 2 displays smoothed rainfall graphs for India’s five meteorological regions, highlighting the spatial variation. Providing more detail, Figure 4 maps district rainfall from the previous decade, at four snapshots in time.\footnote{I choose rainfall from the previous decade as a rough measure of the current monsoon regime (Kripalani and Kulkarni, 1997).} The spatial variation in recent rainfall allows me to include year fixed effects in my regressions and, hence, distinguish rainfall adaptation from time trends in irrigation and crop choice.

## 3 Theoretical Framework

I now derive tests for farmer adaptation. Sections 3.1 and 3.2 outline the climate and agricultural models, respectively. Section 3.3 shows the farmer’s maximization problem, and Section 3.4 presents the adaptation tests.

### 3.1 Climate Model

I model the monsoon regimes as a hidden Markov process. Let $s_t$ indicate the monsoon regime in year $t$, with $s_t = 0$ denoting a dry regime and $s_t = 1$ denoting a wet regime. Year $t$ rainfall can be written as:
\[ r_t = \theta_0 + \delta s_t + u_t, \tag{1} \]

where \( \theta_0 \) is the average rainfall during a dry regime, \( \theta_0 + \delta \) is the average wet regime rainfall, and \( u_t \) represents year-to-year rainfall variability. The monsoon regimes are persistent but not permanent, and they switch according to a Markov process. During a dry regime, the probability of switching to a wet regime during the next period is \( p_0 \). During a wet regime, the probability of switching to a dry regime is \( p_1 \). Each year, farmers observe \( r_t \) and use this information to update their belief about the current regime state, which they do not observe. A farmer’s belief about the current regime state determines his expectation of the next period’s rainfall.

### 3.2 Agricultural Model

In my model, each farmer lives for two periods. In each period \( t \), the farmer allocates his wealth \( w_t \) between an irrigation asset \( i_t \) and another agricultural asset \( a_t \), such that \( a_t + i_t = w_t \).\(^9\) The farmer also chooses a crop portfolio each period. The farmer has one unit of land, which he divides between a drought-tolerant crop and a crop that is relatively more sensitive to drought. Let \( \rho_t \) be the area planted with the drought-tolerant crop, and let \( 1 - \rho_t \) be the drought-sensitive crop area.

Profits are determined by the asset mix, the crop portfolio, and rainfall \( r_t \). I assume a quadratic profit function of the form:

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

where \( \pi_t \) is profits per acre and \( \epsilon_t \) is a mean zero productivity shock. To establish my adaptation tests, I assume that:

1. Profits are increasing in rainfall: \( \delta_r > 0 \). This assumption is consistent with earlier work on India (Jayachandran, 2006; Cole et al., 2012), and I verify it in Section 6.1.

\(^9\)Examples of other agricultural assets include tractors, tillers, ploughs, threshers, and livestock. I abstract away from the possibility of credit markets and non-agricultural assets.
2. The return to irrigation is higher during periods of low rainfall: $\delta_{ir} < 0$. This assumption, while intuitive, is also verified in Section 6.1.

3. The drought-tolerant crop is less profitable, on average, than the drought-sensitive crop: $\beta_{\rho} < 0$. This assumption is necessary to ensure that farmers do not plant all their land with the drought-tolerant crop.

4. Low rainfall reduces the profitability of the drought-tolerant crop less than it reduces the profitability of the drought-sensitive crop: $\delta_{\rho r} < 0$. This assumption comprises my definition of the drought-tolerant crop.

### 3.3 Maximization Problem

Each farmer maximizes:

$$u(c_1) + \beta E_1[u(c_2)]$$

subject to

$$c_1 = w_1 + \pi_1 - w_2 \text{ and } c_2 = w_2 + \pi_2,$$

where $0 < \beta < 1$. For tractability, I assume constant absolute risk aversion utility of the form:

$$u(c_t) = -e^{-\eta c_t}.$$

The timing of the model is as follows. To begin, the farmer chooses his first-period asset mix and crop portfolio, based on initial wealth and initial rainfall expectations. Next, first-period rainfall occurs and first-period profits are determined. With these profits in hand, the farmer chooses how much to consume in the first period and how much wealth to bring into the second period. The farmer also chooses his second-period asset mix and crop portfolio. Lastly, second-period rainfall occurs, and second-period profits are determined.
3.4 Tests for Adaptation

I now derive tests to determine whether farmers are updating their rainfall expectations in response to past rainfall and whether they are adapting their agricultural decisions accordingly. I lack data on farmer rainfall expectations, but the structure of my model allows me to test for adaptation, even without explicit data on expectations.

To clarify the analysis, I introduce the following notation. Let $\mu_1 = E_0(r_1)$ and $\mu_2 = E_1(r_2)$ denote rainfall expectations. Let $w^*_2$ denote the optimal amount of wealth to bring into second-period wealth. Let $i^*_2$ and $\rho^*_2$ denote the optimal second-period irrigation and crop choice decisions. Note that $i^*_2$ and $\rho^*_2$ depend solely on $\mu_2$ and $w^*_2$. Furthermore, $w^*_2$ itself is a function of $w_1$, $\mu_1$, $r_1$ and $\mu_2$.

3.4.1 Tests for Irrigation Adaptation

To begin, note that the total derivative of second-period irrigation with respect to first period rainfall is:

$$\frac{di^*_2}{dr_1} = \frac{\partial i^*_2}{\partial w^*_2} \frac{dw^*_2}{dr_1} + \frac{\partial i^*_2}{\partial \mu^*_2} \frac{d\mu^*_2}{dr_1}$$

Rearranging terms, we get:

$$\frac{di^*_2}{dr_1} = \frac{\partial i^*_2}{\partial w^*_2} \frac{dw^*_2}{dr_1} + \left[ \frac{\partial i^*_2}{\partial \mu^*_2} \frac{d\mu^*_2}{dr_1} \right]$$

I have written the response of second-period irrigation to first-period rainfall as the sum of a wealth effect and an expectations effect. In Section C of the supplementary file, I demonstrate that the signs of the partial derivatives in this expression are:

$$\frac{\partial i^*_2}{\partial w^*_2} > 0, \frac{\partial i^*_2}{\partial \mu^*_2} < 0, \frac{\partial w^*_2}{\partial r_1} > 0, \frac{\partial w^*_2}{\partial \mu^*_2} < 0.$$
The intuitions behind these partial derivatives are: 1) higher second-period wealth induces higher investment in irrigation; 2) higher expected rainfall reduces investment in irrigation; 3) higher first-period rainfall causes the farmer to bring more wealth into the second period; and 4) higher expected rainfall reduces the amount of wealth brought into the second period. The first result occurs because higher second-period wealth increases investment in both assets. The last result is due to consumption smoothing across the two periods.

Taken together, the signs of these partial derivatives imply that, for irrigation, the wealth effect is positive and the expectations effect is negative. As intuition would suggest, the positive wealth effect is generated because higher first-period rainfall increases second-period wealth, which increases investment in both assets, including irrigation. Similarly, the negative expectations effect arises because higher first-period rainfall increases the farmer’s expectation of second-period rainfall, which reduces investment in irrigation.

Having separated the influences of wealth and expectations, I present two tests for whether farmers are adapting their irrigation in response to expected rainfall.

**Proposition 3.1** If farmers increase their irrigation investment after low rainfall, this demonstrates adaptation: \( \frac{d\mu_2^*}{dr_1} < 0 \) implies \( \frac{d\mu_2^*}{dr_1} > 0 \)

**Proposition 3.2** If, conditional on wealth, farmers increase their irrigation investment after low rainfall, this also demonstrates adaptation: \( \left. \frac{d\mu^*_2}{dr_1} \right|_{w_2=\text{constant}} < 0 \) implies \( \frac{d\mu^*_2}{dr_1} > 0 \)

Proposition 3.1 is an unconditional test that does not require accounting for wealth. Proposition 3.1 is useful because it allows me to test for adaptation, even in data sets that lack information on wealth. This is relevant to this study because my two data sets differ in this regard. As Section 4 will explain, my household data set includes data on wealth, but my district data set does not. On the other hand, Proposition 3.2 is a conditional test that incorporates a measure of wealth. It is a more powerful test than Proposition 3.1. If farmers are adapting, but the size of the wealth effect dominates the expectation effect, then Proposition 3.2 will detect the presence of adaptation but Proposition 3.1 will not. Additionally, because Proposition 3.2 separates out the wealth and
expectations effects, the empirical analog of Proposition 3.2 can more accurately estimate the magnitude of the expectation effect. Proposition 3.1, on the other hand, conflates the wealth and expectation effects and so, when estimated, it will understate the size of the expectation effect.

3.4.2 Test for Crop Adaptation

Lastly, I derive a test for crop adaptation. I take the derivative of second-period drought-tolerant crop area with respect to first-period rainfall. Rearranging terms, I get:

$$
\frac{d \rho^*_2}{d r_1} = \frac{\partial \rho^*_2}{\partial w^*_2} \frac{\partial w^*_2}{d r_1} + \left[ \frac{\partial \rho^*_2}{\partial w^*_2} \frac{\partial w^*_2}{\partial \mu^*_2} + \frac{\partial \rho^*_2}{\partial \mu^*_2} \right] \frac{d \mu^*_2}{d r_1}
$$

wealth effect

expectations effect

In Section C of the supplementary file, I demonstrate the following signs of the partial derivatives:

$$
\frac{\partial \rho^*_2}{\partial w^*_2} < 0, \frac{\partial \rho^*_2}{\partial \mu^*_2} < 0, \frac{\partial w^*_2}{\partial \mu^*_2} > 0, \frac{\partial \mu^*_2}{\partial \mu^*_2} < 0.
$$

The first inequality arises because higher wealth reduces a farmer’s risk aversion, which increases his willingness to plant a riskier crop portfolio with less drought-tolerant crop area. The second inequality captures the fact that having higher rainfall expectations will reduce the area a farmer plants with the drought-tolerant crop. The latter two inequalities have been discussed above. Substituting in these partial derivatives, I find that, for crop choice, the wealth effect is negative and the sign of the expectations effect is ambiguous. Therefore, it is not possible to test for crop adaptation without controlling for wealth. On the other hand, if I hold wealth constant, this removes the wealth effect and makes the sign of the expectations effect unambiguously negative. This generates the following test for adaptation:

**Proposition 3.3** If, conditional on wealth, farmers plant a greater area of drought-tolerant crops after low rainfall, this demonstrates adaptation to climate: $\frac{d \rho^*_2}{d r_1} \bigg|_{w^*_2=\text{constant}} < 0$, then $\frac{d \mu^*_2}{d r_1} > 0$

The necessity of controlling for wealth means that I can test for crop adaptation in my house-
hold data set but not in my district data set. Without a wealth control, a negative correlation between lagged rainfall and drought-tolerant crop areas could be occurring solely through a wealth channel and, hence, would not provide evidence of adaptation.\textsuperscript{10}

4 Data Sources and Summary Statistics

I test my model with two agricultural data sets: a household panel and a district panel. The household panel, the Rural Economic and Demographic Survey, was collected by the National Council of Applied Economic Research (NCAER).\textsuperscript{11} The data covers three rounds (1970/71, 1981/82, and 1998/99), with roughly 5,000 household in the first two rounds and 7,500 households in the third. Each round surveys the original households and any new households that have split off from them, as well as a small random sample of new households. I restrict my analysis to households that either were surveyed in multiple rounds or split off from a previously surveyed household. The survey includes data on irrigation, crop areas, assets, wealth, profits, and inherited assets. The district panel, the India Agriculture and Climate Data Set, was compiled by a World Bank research group and covers 271 districts across 14 states for each year between 1956 and 1987 (Sanghi et al., 1998). The data set includes information on irrigated areas, crop areas, crop yields, and prices, but does not include information about assets, wealth, or profits.

I merge the agricultural data with gridded weather data from the Terrestrial Precipitation: Monthly Time Series (1900–2008), version 2.01, and the companion Terrestrial Air Temperature data set.\textsuperscript{12} The weather data for each 0.5 degree latitude–longitude grid point measure combines information from 20 nearby weather stations, using an interpolation algorithm based on the spherical version of Shepard’s distance-weighting method. To merge the weather data with my household data set, I use the rainfall from the weather grid point nearest to each village. For the district data

\textsuperscript{10}Although the district crop choice regressions are not informative, I have analyzed them (results not reported). I found a small but positive correlation between lagged rainfall and drought-tolerant crop areas. The first term of the expectations effect, which is positive if wealth is not controlled for, may cause this.

\textsuperscript{11}The data can be downloaded from http://adfdell.pstc.brown.edu/arisreds_data/.

\textsuperscript{12}Kenji Matsuura and Cort J. Willmott, at the Center for Climatic Research, University of Delaware, constructed the data sets with support from IGES and NASA.
set, I use the rainfall from the grid point nearest to the district center.

Table 1 presents the summary statistics for both data sets. For the household data, I define irrigation investment as a dummy variable for whether the household invested in irrigation during the survey recall period.\textsuperscript{13} The district data lacks direct information on irrigation investment, so I define irrigation investment as the log of the one-year change in the area of irrigated land. To measure the drought-tolerance of a crop portfolio, I draw on information from the agronomists at the Food and Agriculture Organization of the United Nations (FAO). The agronomists quantify the water-intensiveness of a crop with two distinct parameters: water need and drought sensitivity. A crop’s water need is the amount of water it needs for optimal growth, in terms of millimeters per growing season, given as a range. A crop’s drought-sensitivity, on the other hand, measures how much it diminishes a crop’s yield if it doesn’t receive its optimal water requirement. Table 2 presents these values. I calculate a crop portfolio’s water need using the median water needs values, weighted by crop area. I define drought-tolerant (drought-sensitive) crop area as the proportion of area planted with crops that are labeled as having a “low” (“high”) drought-sensitivity.\textsuperscript{14}

I use several different rainfall measures, all of which are based on growing season rainfall.\textsuperscript{15} I measure current rainfall as the z-score deviation from that location’s historical mean. My key explanatory variable is recent average rainfall, defined as the simple average of the rainfall z-scores from the past decade. I also run another specification where I measure lagged rainfall as the number of especially wet or especially dry years over the past decade. The second measure tabulates the proportion of years in the past decade that were especially wet or especially dry. Following Jayachandran (2006), I use the 20th percentile as the cut-off for a dry year and the 80th percentile as the cut-off for a wet year. I choose these lagged decadal rainfall measures as a rough indicator of the current monsoon regime.\textsuperscript{16}

\textsuperscript{13}The recall period is the previous twelve months.
\textsuperscript{14}Because sugarcane is almost exclusively irrigated and also has a much higher water need than other crops grown, I exclude it from my crop water need and drought-sensitivity measures.
\textsuperscript{15}Based on the state-specific monthly rainfall charts in Pant and Kumar (1997), the growing season is defined as June through September for most of the country, and June through December for the Peninsular region (located in the south).
\textsuperscript{16}In Section A.1 of the supplementary file, I verify that my regressions are robust to using an alternate 5- or 15-year rainfall window.
For the household data set, I measure wealth as the sum of the value of irrigation assets, farm equipment, livestock, non-farm assets, housing, durable goods, and financial assets minus debts.17 For the household data set, agricultural profits per acre are measured as crop receipts minus crop expenses, divided by the area of land cultivated. The World Bank data set lacks information on crop expenses. Instead, I use crop revenue per acre of land cultivated.

5 Empirical Strategy

5.1 The Returns to Irrigation

I begin by estimating the effects of irrigation and rainfall on profits. To verify the assumptions from Section 3.2, I need to demonstrate that higher rainfall both increases profits and reduces the returns to irrigation. I run the following regression for agricultural households:

\[
\pi_{ijt} = \beta_1 \text{rain}_{jt} + \beta_2 \text{propirr}_{ijt} + \beta_3 \text{rain}_{jt} \times \text{propirr}_{ijt} + \beta_4 \text{wealth}_{ijt} + \\
+ \beta_5 \text{temperature}_{jt} + \delta_t + \kappa_{ij} + \epsilon_{ijt}.
\]

(6)

The dependent variable \(\pi_{ijt}\) is agricultural profits per acre for household \(i\), in village \(j\), in year \(t\). The explanatory variables are current rainfall \(\text{rain}_{jt}\), the proportion of irrigated land \(\text{propirr}_{ijt}\), wealth \(\text{wealth}_{ijt}\), temperature \(\text{temperature}_{jt}\), a year fixed effect \(\delta_t\), a household fixed effect \(\kappa_{ij}\), and an error term \(\epsilon_{ijt}\) that includes all (non-weather) productivity shocks. The household survey follows households after household splits and after changes of the household head. Therefore, my household fixed effect is common to all parts of the household dynasty that have broken off from the original surveyed household.

Despite the household fixed effects, \(\text{propirr}_{ijt}\) is endogenous in equation 6 if households can adjust their irrigation investments in response to the current productivity shock \(\epsilon_{ijt}\). To address this, I instrument for \(\text{propirr}_{ijt}\) with \(\text{inhpropirr}_{ijt}\), the proportion of inherited land that was irrigated at the time of inheritance. Due to household splits, each dynasty includes multiple household

17I do not include the value of land because land markets in India are inactive and land prices are unreliable. I deflate wealth values to 1971 rupees.
heads, each of whom may inherit a different amount of land at the time he becomes head.\textsuperscript{18} Thus, \( inhpropirr_{ijt} \) has variation, even in the presence of the household fixed effect. Furthermore, although \( inhpropirr_{ijt} \) is likely to be correlated with unobserved household characteristics, including the household fixed effect removes this correlation. Conditional on the fixed effect, \( inhpropirr_{ijt} \) will be correlated with productivity shocks at the time of the inheritance, but not with current-period productivity shocks. This satisfies the exclusion restriction. Earlier work has used the same instrumental variables strategy (Foster and Rosenzweig, 1995, 2001, 2010).

Similarly, \( wealth_{ijt} \) may be endogenous in equation 6 if current-period productivity shocks are correlated with lagged productivity shocks (since lagged productivity shocks affect wealth). I instrument for \( wealth_{ijt} \) with \( inhwealth_{ijt} \), the amount of wealth that was inherited at the time of household formation. As above, household splits allow me to identify \( inhwealth_{ijt} \) even in the presence of the fixed effects. The variable \( inhwealth_{ijt} \) will be correlated with unobserved household characteristics, but this correlation will be absorbed in the fixed effect. Conditional on the fixed effect, inherited wealth will be correlated with productivity shocks at the time of inheritance, but not with current period productivity shocks.

Due to limitations, my district regression is a modified version of equation 6. The unit of observation for the regression is district \( j \) in year \( t \). I use agricultural revenue per acre \( revenue_{jt} \) as the dependent variable. I do not control for wealth. I include \( propirr_{jt} \), but do not instrument for it. The household fixed effect becomes a district fixed effect \( \kappa_{j} \).

For both data sets, finding \( \beta_1 > 0 \) and \( \beta_3 < 0 \) will confirm the assumptions of Section 3.2, namely that higher rainfall increases profits and also reduces the returns to irrigation.

### 5.2 Tests for Irrigation Adaptation

I next analyze how irrigation investment responds to lagged rainfall:

\[
irr\_inv_{ijt} = \alpha_1 decaderain_{jt} + \alpha_2 rain_{jt} + \lambda_t + \mu_{ij} + \zeta_{ijt}.
\]  

\textsuperscript{18}Typically at the time of a father’s death, each son will inherit land and become head of his own separate household (Fernando, 2014).
In the household specification, \( \text{irr}_{ijt} \) is a dummy variable equal to 1 if, during the recall period, a household purchased irrigation equipment or used labor to create/improve irrigation assets.\(^{19}\) The explanatory variables are past decade rainfall \( \text{decaderain}_{jt} \), current year rainfall \( \text{rain}_{jt} \), a year fixed effect \( \lambda_t \), a household fixed effect \( \mu_{ij} \), and an error term \( \zeta_{ijt} \). I measure \( \text{decaderain}_{jt} \) in two ways. The first measure is a simple average of the rainfall z-scores from the past decade. The second measure tabulates the proportion of years in the past decade that were especially wet or especially dry. Following Jayachandran (2006), I use the 20th percentile as the cut-off for a dry year and the 80th percentile as the cut-off for a wet year.

The coefficient of interest in this regression is \( \alpha_1 \). My model demonstrates that the sign of \( \alpha_1 \) is ambiguous and must be determined empirically. If the wealth effect dominates, then \( \alpha_1 \) will be positive. Irrigation investment will increase after wet decades, due to an accumulation of wealth and increased investment in all assets. On the other hand, if farmers are adapting to expected rainfall and the size of this effect is larger than the wealth effect, then we will find \( \alpha_1 < 0 \). Irrigation investment will increase after dry decades, due to farmers expecting more dry years in the future. Thus, finding \( \alpha_1 < 0 \) provides evidence of adaptation.\(^{20}\)

I control for current year rainfall because farmers can invest in irrigation at any time during the year. Thus, a farmer’s observation of current year rainfall (based on, say, the first half of the growing season) might directly affect his decision to invest in irrigation that period. This response would not indicate adaptation to expected future year rainfall, but would simply reveal within-season adjustment to current year rainfall.

Propositions 3.1 and 3.2 demonstrate that I can test for irrigation adaptation with or without a wealth control. Thus, for completeness, I run a second household specification where I control for wealth. Once I have isolated the wealth effect, my model predicts that \( \alpha_1 = 0 \) if farmers are not adapting. On the other hand, if farmers are adapting, then \( \alpha_1 < 0 \). The variable \( \text{wealth}_{ijt} \) is endogenous in this regression, and so I instrument it with \( \text{inhwealth}_{ijt} \). The validity of the

\(^{19}\)I do not use the rupee value of investment, because a large component of it is family labor, the value of which is measured with a lot of noise.

\(^{20}\)Finding a positive coefficient would be inconclusive; it would neither demonstrate, nor rule out, the possibility of adaptation.
instrument follows the same logic as for equation 6.

For my district regression, I define \( \text{irr}_{\text{inv}ij} \) as the log of the one-year change in the district’s irrigated area, I use a district fixed effect, and I do not control for wealth. Proposition 3.1 demonstrates that I can test for irrigation adaptation, even in the absence of a wealth control. As with the household regression, finding \( \alpha_1 < 0 \) provides evidence of adaptation.

5.3 Test for Crop Adaptation

Lastly, I test for crop adaptation. I only perform this test with my household data set, and my regression is of the form:

\[
crop_{\text{var}ijt} = \gamma_1 \text{decaderain}_{jt} + \gamma_2 \text{rain}_{jt} + \gamma_3 \text{propirr}_{ijt} + \gamma_4 \text{wealth}_{ijt} + \\
+ \tau_t + \phi_{ij} + \psi_{ijt},
\]

where \( \text{crop}_{\text{var}ijt} \) is the water-intensiveness of the crop portfolio. I use three different parameters for \( \text{crop}_{\text{var}ijt} \): the average crop water need of the portfolio, the proportion of land planted with drought-sensitive crops, and the proportion land planted with drought-tolerant crops. Section 4, above, gives more details on the construction of these variables.

As mentioned above, I control for current year rainfall because farmers may have some knowledge of the current year rainfall before they sow all of their crops. As in the irrigation regression, a response of crop choice to current year rainfall would indicate a within-season adjustment to rainfall, but would not provide evidence of adaptation to expected future year rainfall. I also control for \( \text{propirr}_{ijt} \) because the proportion of irrigated land will influence the crops planted. I instrument for \( \text{propirr}_{ijt} \) with \( \text{inhpropirr}_{ijt} \), the proportion of inherited land that was irrigated at the time of inheritance. My instrumental variable strategy for \( \text{propirr}_{ijt} \) in equation 8 follows the same logic as the IV strategy for \( \text{propirr}_{ijt} \) in equation 6. I also control for \( \text{wealth}_{ijt} \) because, as demonstrated in Section 3.4.2, without a control for \( \text{wealth}_{ijt} \), I could not interpret \( \gamma_1 \) as evidence of adaptation. Instead, drought-sensitive crop areas might increase after wet decades because of a wealth increase that has reduced risk aversion. As in the above equations, wealth is endogenous, and so I instru-
ment for it with inherited wealth. Finding $\gamma_1 = 0$ demonstrates that farmers are not adapting their crop portfolios. Conversely, in the presence of adaptation, I expect to find $\gamma_1 > 0$ for the crop water need and drought-sensitive regressions, and $\gamma_1 < 0$ for the drought-tolerant regression.

6 Results

6.1 The Returns to Irrigation

Table 3 tests the impacts of rainfall and irrigation on profits. In the household regressions, shown in columns 1 and 2, the dependent variable is profits per acre. In column 1, I deduct the value of family labor, and in column 2, I do not. I measure rainfall using quintiles to allow for non-linear effects. I instrument for the proportion of irrigated land with the proportion of inherited irrigated land.\(^{21}\) In the district regression, shown in column 3, the dependent variable is revenue per acre, and I do not instrument for irrigation. For both data sets, the coefficients demonstrate that higher rainfall increases profits and that the returns to irrigation rise during dry years, thus confirming the assumptions of Section 3.2. In Table 3, and all the tables below, standard errors are clustered at the rainfall grid-point level, to allow for shared measurement error in rainfall.

6.2 Tests for Irrigation Adaptation

Table 4 tests whether farmers are adapting their irrigation investments in response to lagged rainfall. Recall that I can test for irrigation adaptation either with, or without, a wealth control. Columns 1 through 4 use the household data and, in columns 2 and 4, I control for wealth, which is instrumented for with inherited wealth. Columns 5 and 6 use the district data and do not control for wealth. In all columns, I find the coefficient of lagged rainfall is negative, which provides evidence of adaptation. In terms of magnitudes, column 3 demonstrates that a dry year in the preceding decade increases the probability of irrigation investment during the recall period by 1.2 percentage

\(^{21}\)The F-statistics, presented at the bottom of the table, indicate that the first-stage regressions are sufficiently strong.
points. The baseline probability of investing in irrigation during the recall period is 5%.22

6.3 Test for Crop Adaptation

In Table 5, I test for crop adaptation using the household data set. In all columns, I control for wealth and for the proportion of irrigated land. I instrument for these variables with inherited wealth and the inherited proportion of irrigated land.23 Using either rainfall measure (average rainfall or wet/dry shocks), I find that farmers plant portfolios with higher water needs after wet decades. Using the wet/dry shock measure, I find that farmers plant less area to drought-sensitive crops after dry decades, but this result is not robust to using the average rainfall measure. Lastly, I do not find that drought-tolerant crop areas respond to lagged rainfall. Looking at column 6, an additional dry year in the past decade decreases the area planted with drought-sensitive crops by 1.9 percentage points, relative to a baseline of 37% of area planted with drought-sensitive crops.

The agronomy literature states that the impact of crop water need on yields is modulated primarily by total growing season rainfall. The impact of drought-sensitivity on yields, on the other hand, is driven primarily by intraseasonal rainfall variability, such as the duration of monsoon break periods (dry spells) during the season (Sharma et al., 2008). This suggests that the water need results in columns 1 and 2 may be of the most interest. Nevertheless, due to the lack of consistency across the different crop measures, I interpret the results in Table 5 as less convincing than the Table 4 results. It may be the case that farmers adapt their irrigation investments more readily than their crop portfolios.

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22 The F-statistics for columns 2 and 4, presented at the bottom of the table, indicate that the first-stage regressions for wealth are sufficiently strong. For concision, I don’t display the first-stage regression coefficients, but they are available upon request.

23 The F-statistics, presented at the bottom of the table, indicate that the first-stage regressions are sufficiently strong. For concision, I don’t display the first-stage regression coefficients, but they are available upon request.
7 Robustness

In a supplementary file (submitted separately), I investigate the robustness of my results. First, I reestimate my regressions using rainfall lag windows of 5 or 15 years, to verify that the choice of a 10-year window is not driving my results. My results are, for the most part, preserved, although with a loss of precision in some cases. Second, I explore the possibility that groundwater depletion, rather than adaptation, might be causing the relationship between irrigation investment and lagged rainfall that I have found. Using irrigated area (rather than irrigation investment) as my dependent variable, I find that the area of irrigated land increases after dry decades. This is consistent with farmer adaptation but not with a groundwater depletion story. Third, I test whether my irrigation adaptation results might be due to public (government) investments rather than private (farmer) investments. In India, the bulk of irrigation investments are large-scale dams. When I control for the presence of these dams, my irrigation adaptation results are preserved, indicating that these results are not solely driven by public investment. Lastly, I test whether changes in agricultural technology or policies might be confounding my results. I add controls for high-yielding variety crops, electrification rates, fertilizer prices, financial institutions, agricultural extension services, transportation infrastructure, and government intervention in output markets. Again, my adaptation results are preserved, although I lose precision in some cases. The supplementary file provides more details on these tests.

8 Effectiveness of Adaptation

The preceding text has found evidence of adaptation; this section quantifies its efficacy. What fraction of profits were farmers able to protect from adverse climate variations? To answer this question, I use the household data set to estimate the extent to which irrigation adaptation increased profits during 1971–1999. Rainfall during this period was below average (as shown in Figure 1),

---

24 The analysis focuses on irrigation adaptation because the efficacy of crop adaptation is not calculable. Specifically, the data do not permit an unbiased estimate of the impact of crop portfolio on profits. Unobserved shocks, such as health shocks, may be correlated with both profits and drought-tolerant crop areas, and hence a regression of profits...
and this reduced profits. To calculate the efficacy of adaptation, I estimate, first, the percentage of
profits that were lost due to dry rainfall and, second, the percent of these losses that were recovered
via adaptation. I use profits from three different scenarios: actual profits, counterfactual profits
under a scenario where the dry regime did not occur, and counterfactual profits under a scenario
where the dry regime occurred but farmers did not adapt.

For each scenario, the regression coefficients from Table 3, column 2, are used to calculate
the profits per acre for a given set of weather, irrigation, and wealth outcomes. To estimate actual
profits for non-survey years, I use the actual rainfall and interpolated values of wealth and irrigated
land. For the counterfactual scenario where the dry regime did not occur, I calculate expected
annual profits, using a 20% chance of each rainfall quintile occurring. This calculation effectively
projects what expected profits would have been if rainfall was at its historical mean distribution. I
interpolate irrigation and wealth for non-survey years for this counterfactual scenario as well.

Lastly, I calculate counterfactual profits under a scenario where the dry regime occurred but
farmers did not adapt their irrigation. I use the actual weather realizations and interpolated wealth.
For irrigation, I use a counterfactual value of what the proportion of irrigated land would have
been in the absence of adaptation. I use the coefficients from column 1 of Table 6 to calculate the
adaptive response of irrigation to lagged rainfall. This table is analogous to my baseline irrigation
adaptation specification (Table 4) but uses the proportion of irrigated land as the dependent variable
(rather than an irrigation investment dummy). The irrigation investment dummy captures precisely
how the household, this year, is adjusting its irrigation. However, using it requires knowing what
fraction of the farmer’s land becomes irrigated when he invests in irrigation, since profits depend on
the proportion of land irrigated. Thus, I use instead the proportion of irrigation, which is a coarser
measure of adaptation. This allows me to subtract a quantity of “adapted irrigation” from the
interpolated irrigation, to calculate what irrigation would have been in the absence of adaptation.

Using these profit measures, I find that on net the dry regime decreased farmers’ profits by
0.4%. However, there is substantial heterogeneity among households, and for households with
on drought-tolerant areas will be biased. For irrigation, in contrast, I can instrument for irrigated land with inherited
irrigated land and remove this bias.
losses, the average loss was 3.1%. Furthermore, farmers with profit losses recovered only 13% of their losses on average. Farmer adaptation to persistent rainfall deviations appears to have had limited efficacy. This is suggestive that adaptation to future anthropogenic climate change may be limited. However, extrapolating my results directly to future climate change is problematic, since future climate change will affect both rainfall and temperature.

9 Conclusion

To accurately predict future climate change damages requires an accurate understanding of the ability of agents to adapt to changes in climate. In this paper, I exploit persistent rainfall variations in India over the past 50 years to test whether farmers adjust their irrigation and crop choice decisions in response to recent rainfall. I find solid evidence of irrigation adaptation and more limited evidence of crop adaptation. My results are robust to the inclusion of controls for government irrigation investment, water supply depletion, and changes in agricultural technology and policies. However, analysis suggests that the efficacy of adaptation is limited; adaptation recaptures on average only 13% of lost profits. Limitations include the fact that I look at adaptation to rainfall changes only (not temperature changes) and that this paper has only considered two possible adaptations, when in fact a much broader array of adaptations are possible. Despite these caveats, my results suggest that, in the context of the historical rainfall deviations that I have analyzed, there are barriers to adaptation. My work does not elucidate the precise nature of these barriers. Other work, summarized by Jack (2011), indicates that credit and information constraints, as well as inefficiencies in input, output, land, labor, and risk markets, inhibit agricultural adaptation in a variety of situations. The specific barriers to climate change adaptation and, importantly, the institutions, technologies, and policies that might remove these barriers, call for further exploration.

References


Figure 1: Interdecadal Variability of the Indian Monsoon

Note: This figure displays the 31-year moving average of India’s summer monsoon rainfall, measured as a z-score deviation from the historical mean. Source: The rainfall data are from the India Institute of Tropical Meteorology’s Homogeneous Indian Monthly Rainfall Data Set (1871–2008). The figure is constructed based on the author’s calculations.
Figure 2: Spatial Variation of the Interdecadal Variability of the Indian Monsoon

*Note:* This figure graphs the 31-year moving average of the summer monsoon rainfall, measured in millimeters for India’s five meteorological regions. The horizontal line represents mean rainfall for that region. *Source:* The rainfall data are from the India Institute of Tropical Meteorology’s Homogeneous Indian Monthly Rainfall Data Set (1871–2008). The figure is constructed based on the author’s calculations.
Figure 3: Annual Variability of the Indian Monsoon

Note: The y-axis graphs the All-India summer monsoon rainfall, expressed as a z-score deviation from its historical mean. Source: The rainfall data are from the India Institute of Tropical Meteorology’s Indian Monthly Rainfall Data Set (1871–2008). The figure is constructed based on the author’s calculations.
Figure 4: Spatial Variation in Decadal Rainfall

*Note:* The map displays average (z-score) summer rainfall for each district over the previous decade. Blue represents higher rainfall, and red represents lower rainfall. *Source:* The rainfall data are from the India Institute of Tropical Meteorology’s Homogeneous Indian Monthly Rainfall Data Set (1871–2008). The figure is constructed based on the author’s calculations.
Table 1: Summary Statistics

<table>
<thead>
<tr>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Agricultural profits per acre (1971 Rs.)</td>
<td>502.96 (440.9)</td>
<td>586.6 (654.9)</td>
<td>741.7 (940.0)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Agricultural profits per acre, deducting the value of family labor (1971 Rs.)</td>
<td>- (530.9)</td>
<td>375.3 (819.2)</td>
<td>425.3 (940.0)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Agricultural revenue per acre</td>
<td>-</td>
<td>-</td>
<td>-</td>
<td>4425.6 (2070.2)</td>
<td>1439.5 (637.3)</td>
<td>15340.0 (4796.9)</td>
</tr>
<tr>
<td>Proportion of land irrigated</td>
<td>0.378 (0.437)</td>
<td>0.414 (0.455)</td>
<td>0.483 (0.466)</td>
<td>0.234 (0.203)</td>
<td>0.178 (0.175)</td>
<td>0.321 (0.256)</td>
</tr>
<tr>
<td>Irrigation investment during the recall period (dummy)</td>
<td>0.0767 (0.266)</td>
<td>0.0724 (0.259)</td>
<td>0.0116 (0.107)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Log non-land wealth (1971 Rs.)</td>
<td>8.065 (1.081)</td>
<td>7.040 (1.406)</td>
<td>9.123 (1.228)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Average crop water need (millimeters)</td>
<td>- (67.69)</td>
<td>576.4 (82.86)</td>
<td>583.8 (82.86)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Proportion of area planted with drought-tolerant crops</td>
<td>-</td>
<td>0.264 (0.340)</td>
<td>0.166 (0.314)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
<tr>
<td>Proportion of area planted with drought-sensitive crops</td>
<td>-</td>
<td>0.392 (0.391)</td>
<td>0.476 (0.395)</td>
<td>-</td>
<td>-</td>
<td>-</td>
</tr>
</tbody>
</table>

<table>
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<tr>
<th></th>
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<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Current year rainfall</td>
<td>0.313 (0.929)</td>
<td>0.208 (0.772)</td>
<td>0.279 (0.723)</td>
<td>0.436 (1.007)</td>
<td>0.579 (0.883)</td>
<td>-0.400 (0.748)</td>
</tr>
<tr>
<td>Ten-year lagged average rainfall</td>
<td>-0.000634 (0.328)</td>
<td>0.0653 (0.251)</td>
<td>-0.0303 (0.326)</td>
<td>0.000608 (0.288)</td>
<td>0.108 (0.294)</td>
<td>-0.0353 (0.234)</td>
</tr>
<tr>
<td>Ten-year lagged average of dry shock</td>
<td>0.196 (0.125)</td>
<td>0.183 (0.0925)</td>
<td>0.166 (0.150)</td>
<td>0.203 (0.122)</td>
<td>0.176 (0.111)</td>
<td>0.191 (0.106)</td>
</tr>
<tr>
<td>Ten-year lagged average of wet shock</td>
<td>0.177 (0.122)</td>
<td>0.220 (0.130)</td>
<td>0.167 (0.124)</td>
<td>0.185 (0.106)</td>
<td>0.224 (0.133)</td>
<td>0.163 (0.115)</td>
</tr>
</tbody>
</table>

Note: The table displays mean coefficients, with standard deviations in parentheses. The household sample is restricted to farmers who cultivate land. See Section 4 for details on how the variables are constructed.
Table 2: Crop Water Needs and Sensitivity to Drought

<table>
<thead>
<tr>
<th>Crop</th>
<th>Water Need</th>
<th>Sensitivity to Drought</th>
</tr>
</thead>
<tbody>
<tr>
<td>Barley</td>
<td>450-650</td>
<td>low-medium</td>
</tr>
<tr>
<td>Cotton</td>
<td>700-1300</td>
<td>low</td>
</tr>
<tr>
<td>Maize</td>
<td>500-800</td>
<td>medium-high</td>
</tr>
<tr>
<td>Millet</td>
<td>450-650</td>
<td>low</td>
</tr>
<tr>
<td>Peanut</td>
<td>500-700</td>
<td>low-medium</td>
</tr>
<tr>
<td>Potato</td>
<td>500-700</td>
<td>high</td>
</tr>
<tr>
<td>Pulses</td>
<td>350-500</td>
<td>medium-high</td>
</tr>
<tr>
<td>Rice</td>
<td>450-700</td>
<td>high</td>
</tr>
<tr>
<td>Sorghum</td>
<td>450-650</td>
<td>low</td>
</tr>
<tr>
<td>Soybean</td>
<td>450-700</td>
<td>low-medium</td>
</tr>
<tr>
<td>Sugarcane</td>
<td>1500-2500</td>
<td>high</td>
</tr>
<tr>
<td>Sunflower</td>
<td>600-1000</td>
<td>low-medium</td>
</tr>
<tr>
<td>Wheat</td>
<td>450-650</td>
<td>low-medium</td>
</tr>
</tbody>
</table>

*Note: Crop water need is measured in millimeters per growing season. Source: Brouwer and Heibloem (1986).*
Table 3: The Impacts of Irrigation and Rainfall on Profits

<table>
<thead>
<tr>
<th>Data set:</th>
<th>Household FE-IV</th>
<th>Household FE-IV</th>
<th>District FE</th>
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<tbody>
<tr>
<td>Specification:</td>
<td>----------------</td>
<td>----------------</td>
<td>------------</td>
</tr>
<tr>
<td>Dependent variable:</td>
<td>Profits per Acre</td>
<td>Profit per Acre</td>
<td>Revenue per Acre</td>
</tr>
<tr>
<td>Rainfall below 20th percentile (dummy)</td>
<td>3.154 (136.3)</td>
<td>-55.14 (149.1)</td>
<td>-471.6*** (122.7)</td>
</tr>
<tr>
<td>Rainfall between 20th and 40th percentiles</td>
<td>87.84 (93.98)</td>
<td>82.21 (101.8)</td>
<td>-272.1** (121.5)</td>
</tr>
<tr>
<td>Rainfall between 60th and 80th percentiles</td>
<td>155.9* (81.19)</td>
<td>90.90 (87.36)</td>
<td>108.0 (106.5)</td>
</tr>
<tr>
<td>Rainfall above 80th percentile</td>
<td>313.2*** (82.55)</td>
<td>336.1*** (85.16)</td>
<td>127.9 (114.3)</td>
</tr>
<tr>
<td>Proportion of irrigated land</td>
<td>364.2*** (126.6)</td>
<td>430.4*** (141.9)</td>
<td>3031.7*** (900.3)</td>
</tr>
<tr>
<td>Propirr*Rainfall below 20th percentile</td>
<td>-216.7 (170.6)</td>
<td>-125.0 (189.0)</td>
<td>1001.0** (468.9)</td>
</tr>
<tr>
<td>Propirr*Rainfall between 20th and 40th percentiles</td>
<td>-251.8 (168.1)</td>
<td>-188.6 (174.0)</td>
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<td>Propirr*Rainfall between 60th and 80th percentiles</td>
<td>-157.2 (139.5)</td>
<td>-87.84 (151.1)</td>
<td>-295.1 (390.1)</td>
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<td>Propirr*Rainfall above 80th percentile</td>
<td>-451.4*** (199.1)</td>
<td>-466.8** (223.8)</td>
<td>-227.4 (397.6)</td>
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<td>Temperature</td>
<td>-16.06 (32.52)</td>
<td>-32.42 (39.91)</td>
<td>-174.2*** (46.58)</td>
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<td>Log non-land wealth (1971 Rs.)</td>
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<td>73.27 (63.34)</td>
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<td>District Yes</td>
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<td>6828</td>
<td>8384</td>
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<td>First stage</td>
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<td>$F$ statistic (Proportion of irrigated land)</td>
<td>92.51</td>
<td>92.51</td>
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<tr>
<td>$F$ statistic (Log non-land wealth)</td>
<td>19.96</td>
<td>19.96</td>
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</table>

Notes: Standard errors, in parentheses below the coefficients, allow for clustering within a latitude-longitude grid point. Column 1 deducts the value of family labor from profits and column 2 does not. In columns 1 and 2, I instrument for the proportion of irrigated with the proportion of inherited land that was irrigated, and I instrument for wealth with inherited wealth. The first-stage F-statistics are reported in the table. Full first-stage regressions are also available from the author. F-test: The Staiger and Stock (1997) rule of thumb is that instruments are “weak” if the first-stage F is less than 10, and the Stock and Yogo (2002) Weak ID test critical value for 2SLS bias being less than 10% of OLS bias is 16.38. See Section 4 for details on how the variables are constructed.

$^*$ $p < 0.10$, $^**$ $p < 0.05$, $^***$ $p < 0.01$
Table 4: Testing for Irrigation Adaptation

<table>
<thead>
<tr>
<th>Data set:</th>
<th>Household</th>
<th>Household</th>
<th>Household</th>
<th>Household</th>
<th>District</th>
<th>District</th>
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<tbody>
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<td>Specification:</td>
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<td>FE-IV</td>
<td>FE</td>
<td>FE-IV</td>
<td>FE</td>
<td>FE</td>
</tr>
<tr>
<td>Dependent variable:</td>
<td>Irrigation Investment (Dummy)</td>
<td>Irrigation Investment (Dummy)</td>
<td>Irrigation Investment (Dummy)</td>
<td>Irrigation Investment (Dummy)</td>
<td>Log of the One-Year Change of Irrigated Area</td>
<td>Log of the One-Year Change of Irrigated Area</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
<td>(5)</td>
<td>(6)</td>
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<tr>
<td>Ten-year lagged average rainfall</td>
<td>-0.0543***</td>
<td>-0.0543**</td>
<td>-0.00754***</td>
<td>-0.00754***</td>
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<tr>
<td></td>
<td>(0.0207)</td>
<td>(0.0219)</td>
<td>(0.00212)</td>
<td>(0.00212)</td>
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<tr>
<td>Ten-year lagged average of dry shock</td>
<td>0.119**</td>
<td>0.129**</td>
<td>0.129**</td>
<td>0.129**</td>
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<tr>
<td></td>
<td>(0.0564)</td>
<td>(0.0554)</td>
<td>(0.0554)</td>
<td>(0.0554)</td>
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<tr>
<td>Ten-year lagged average of wet shock</td>
<td>-0.0603</td>
<td>-0.0405</td>
<td>-0.0200***</td>
<td>-0.0200***</td>
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</tr>
<tr>
<td></td>
<td>(0.0504)</td>
<td>(0.0522)</td>
<td>(0.00618)</td>
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<tr>
<td>Current year rainfall</td>
<td>0.00709</td>
<td>0.00823</td>
<td>0.00529</td>
<td>0.00636</td>
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<tr>
<td></td>
<td>(0.00651)</td>
<td>(0.00640)</td>
<td>(0.00654)</td>
<td>(0.00647)</td>
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<td>Log non-land wealth (1971 Rs.)</td>
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<td>0.0478***</td>
<td>0.0478***</td>
<td>0.0478***</td>
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<tr>
<td></td>
<td>(0.0130)</td>
<td>(0.0127)</td>
<td>(0.0127)</td>
<td>(0.0127)</td>
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<td>Household</td>
<td>Household</td>
<td>Household</td>
<td>District</td>
<td>District</td>
</tr>
<tr>
<td>Year fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>First stage</td>
<td>F statistic (Log non-land wealth)</td>
<td>109.73</td>
<td>107.72</td>
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<tr>
<td>Observations</td>
<td>12003</td>
<td>11759</td>
<td>12003</td>
<td>11759</td>
<td>8130</td>
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</tr>
</tbody>
</table>

Note: Standard errors, in parentheses below the coefficients, allow for clustering within a latitude–longitude grid point. A dry shock is defined rainfall below the 20th percentile and a wet shock is defined as rainfall above the 80th percentile. In columns 2 and 4, I instrument for wealth with inherited wealth. The first-stage F-statistics are reported in the table. Full first-stage regressions are also available upon request. F-test: The Staiger and Stock (1997) rule of thumb is that instruments are “weak” if the first-stage F is less than 10, and the Stock and Yogo (2002) Weak ID test critical value for 2SLS bias being less than 10% of OLS bias is 16.38. See Section 4 for details on how the variables are constructed.

*p < 0.10, ** p < 0.05, *** p < 0.01
Table 5: Testing for Crop Adaptation: Household Data Set

<table>
<thead>
<tr>
<th></th>
<th></th>
<th></th>
<th></th>
<th></th>
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<th></th>
</tr>
</thead>
<tbody>
<tr>
<td>Dependent variable:</td>
<td>Crop Water Need</td>
<td>Crop Water Need</td>
<td>Proportion Drought-Tolerant</td>
<td>Proportion Drought-Tolerant</td>
<td>Proportion Drought-Sensitive</td>
<td>Proportion Drought-Sensitive</td>
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<tr>
<td>Ten-year lagged average rainfall</td>
<td>20.65*</td>
<td>-0.0405</td>
<td>0.0237</td>
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</tr>
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<td></td>
<td>(11.81)</td>
<td>(0.0389)</td>
<td>(0.0302)</td>
<td></td>
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<tr>
<td>Ten-year lagged average of dry shock</td>
<td>-32.09</td>
<td>-0.135</td>
<td>-0.194**</td>
<td>-0.194**</td>
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<tr>
<td></td>
<td>(22.57)</td>
<td>(0.111)</td>
<td>(0.0803)</td>
<td></td>
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<td>Ten-year lagged average of wet shock</td>
<td>55.21**</td>
<td>-0.152</td>
<td>0.0230</td>
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<td></td>
<td>(26.29)</td>
<td>(0.0960)</td>
<td>(0.0675)</td>
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<td>Current year rainfall</td>
<td>-1.173</td>
<td>-0.593</td>
<td>0.0175</td>
<td>0.0153</td>
<td>0.00606</td>
<td>0.00591</td>
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<td></td>
<td>(3.816)</td>
<td>(3.698)</td>
<td>(0.0143)</td>
<td>(0.0137)</td>
<td>(0.0123)</td>
<td>(0.0119)</td>
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<tr>
<td>Proportion of irrigated land</td>
<td>-2.734</td>
<td>-2.866</td>
<td>-0.124***</td>
<td>-0.124***</td>
<td>0.0368</td>
<td>0.0369</td>
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<td>(12.17)</td>
<td>(11.85)</td>
<td>(0.0300)</td>
<td>(0.0302)</td>
<td>(0.0338)</td>
<td>(0.0334)</td>
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<tr>
<td>Log non-land wealth (1971 Rs.)</td>
<td>-2.657</td>
<td>-1.784</td>
<td>0.0393**</td>
<td>0.038*</td>
<td>-0.0135</td>
<td>-0.0157</td>
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<td>(5.839)</td>
<td>(5.559)</td>
<td>(0.0192)</td>
<td>(0.0200)</td>
<td>(0.0227)</td>
<td>(0.0213)</td>
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<td>Fixed effects</td>
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<td>Household</td>
<td>Household</td>
<td>Household</td>
<td>Household</td>
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<tr>
<td>Year fixed effects</td>
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<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
<td>Yes</td>
</tr>
<tr>
<td>First stage</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>$F$ statistic (Proportion of irrigated land)</td>
<td>141.01</td>
<td>143.24</td>
<td>132.22</td>
<td>134.29</td>
<td>132.22</td>
<td>134.29</td>
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<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>$F$ statistic (Log non-land wealth)</td>
<td>45.00</td>
<td>47.08</td>
<td>45.27</td>
<td>47.48</td>
<td>45.27</td>
<td>47.48</td>
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<td>5468</td>
<td>5468</td>
<td>5468</td>
<td>5468</td>
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</tbody>
</table>

Note: Standard errors, in parentheses below the coefficients, allow for clustering within a latitude-longitude grid point. A dry shock is rainfall below the 20th percentile and a wet shock is rainfall above the 80th percentile. In all columns, I instrument for the proportion of irrigated with the proportion of inherited land that was irrigated and I instrument for wealth with inherited wealth. The first-stage F-statistics are reported in the table. Full first-stage regressions are also available from the author. F-test: The Staiger and Stock (1997) rule of thumb is that instruments are “weak” if the first-stage F is less than 10, and the Stock and Yogo (2002) Weak ID test critical value for 2SLS bias being less than 10% of OLS bias is 16.38. See Section 4 for details on how the variables are constructed.

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
### Table 6: Testing for Irrigation Adaptation: Dependent Variable is the Proportion of Irrigated Land

<table>
<thead>
<tr>
<th>Data set: Specification:</th>
<th>Household FE</th>
<th>Household FE-IV</th>
<th>Household FE</th>
<th>Household FE-IV</th>
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<tbody>
<tr>
<td>Dependent variable:</td>
<td>Proportion of Irrigated Land</td>
<td>Proportion of Irrigated Land</td>
<td>Proportion of Irrigated Land</td>
<td>Proportion of Irrigated Land</td>
</tr>
<tr>
<td></td>
<td>(1)</td>
<td>(2)</td>
<td>(3)</td>
<td>(4)</td>
</tr>
<tr>
<td>Ten-year lagged average rainfall</td>
<td>-0.0770**</td>
<td>-0.0735***</td>
<td>0.0378 0.0493</td>
<td>(0.0297) (0.0309)</td>
</tr>
<tr>
<td>Ten-year lagged average of dry shock</td>
<td>0.0734 (0.0779)</td>
<td>0.0493</td>
<td>-0.124* -0.0894</td>
<td>(0.0661) (0.0691)</td>
</tr>
<tr>
<td>Ten-year lagged average of wet shock</td>
<td>0.0493</td>
<td>0.0493</td>
<td>-0.0894</td>
<td>(0.0779)</td>
</tr>
<tr>
<td>Current year rainfall</td>
<td>-0.0214*</td>
<td>-0.0203</td>
<td>-0.0240* -0.0228*</td>
<td>(0.0127) (0.0131)</td>
</tr>
<tr>
<td>Log non-land wealth (1971 Rs.)</td>
<td>0.0739*** (0.0165)</td>
<td>0.0715*** (0.0166)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Fixed effects Year fixed effects</td>
<td>Household</td>
<td>Household</td>
<td>Household</td>
<td>Household</td>
</tr>
<tr>
<td>First stage</td>
<td>Household</td>
<td>Household</td>
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<tr>
<td>F statistic (Log non-land wealth)</td>
<td>109.73</td>
<td>107.72</td>
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<td>11759</td>
<td>11858</td>
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</tbody>
</table>

Notes: Standard errors, in parentheses below the coefficients, allow for clustering within a latitude-longitude grid point. A dry shock is rainfall below the 20th percentile and a wet shock is rainfall above the 80th percentile. In columns 2 and 4, I instrument for wealth with inherited wealth. The first-stage F-statistics are reported in the table. Full first-stage regressions are also available from the author. F-test: The Staiger and Stock (1997) rule of thumb is that instruments are “weak” if the first-stage F is less than 10, and the Stock and Yogo (2002) Weak ID test critical value for 2SLS bias being less than 10% of OLS bias is 16.38. See Section 4 for details on how the variables are constructed.

* \( p < 0.10 \), ** \( p < 0.05 \), *** \( p < 0.01 \)