CAN FARMERS ADAPT TO HIGHER TEMPERATURES?

EVIDENCE FROM INDIA

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Abstract

Forecasts suggest climate change will have large negative impacts on developing countries. The extent to which households in these countries will be able to adapt to climate change will determine a large portion of this impact. In this paper, I investigate the ability of farmers in India to adapt to increases in temperature. I use a methodology that exploits both short-term weather fluctuations and long-run climate variations. Specifically, I estimate how damaging high temperatures are for districts that experience high temperatures more or less frequently. I find that the losses from increased temperatures are lower in heat-prone districts, a result that is consistent with adaptation. However, while adaptation appears to be modestly effective for moderate levels of heat, my results suggest that adaptation to extreme heat is much more difficult. Extremely high temperatures do grave damage to crops, even in places that experience these temperature extremes regularly. The persistence of negative impacts of high temperatures, even in areas that experience high temperatures frequently, underscores the need for development policies that emphasize risk mitigation and explicitly account for climate-change-related risks.

JEL Classification: O1, O3, Q1, Q5

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1 Introduction

According to the Fifth Assessment Report from the Intergovernmental Panel on Climate Change, it is virtually certain that average temperatures worldwide will increase by the end of the 21st century, and very likely that the frequency and duration of heat waves will increase (Stocker et al., 2013). Poor countries located in low latitudes will likely experience heat extremes first (Harrington et al., 2016). For two reasons, projections suggest damage will be substantial. First, many households in poor countries rely on agriculture, forestry, or fisheries for their livelihoods. Thus their livelihoods inherently rely on the climate. Second, many of these households have limited access to assets and infrastructure that could protect them against climate change.

Looking at agriculture in particular, researchers predict significant climate-induced agricultural damages in developing countries (Guiteras, 2009). The preferred methodology for estimating agricultural damages due to climate change uses short-term fluctuations in weather to construct a yield-temperature relationship, which is then extrapolated to future climate change, based on future predicted changes to the climate. However, reliance on short-term fluctuations does not allow for long-run adaptations that agents may undertake in the face of sustained climate change. Therefore it is critical to understand how easily farmers can adapt to higher temperatures and what the potential barriers to adaptation may be.

In this paper, I exploit spatial and temporal variation in the incidence of high temperatures in India, to estimate the extent to which farmers have adapted to high temperatures. I use a fixed-effects framework to investigate whether farmers in heat-prone areas have adapted to high temperatures and have been able to reduce heat-induced yield losses. I also explore the extent to which this adaptation occurs via inter- or intra-crop farmer behaviors.

I use panel data on agricultural yields for 286 Indian districts during the period 1979–2011, merged with a daily gridded weather data set. I use a flexible temperature-binning approach to measure the impact of higher temperatures on agricultural yields. The analysis begins with estimating the impact of higher temperatures on agricultural yields, while controlling for district-level unobservables. The fixed-effects strategy I employ here is common in the literature (Deschenes
and Greenstone, 2007; Schlenker and Roberts, 2009; Guiteras, 2009; Burgess et al., 2017). The second step consists of dividing the sample into two groups: districts whose long-run average temperature is above the median temperature, and districts whose long-run average temperature is below the median. Then I repeat my fixed-effects strategy of estimating the impact of temperatures on yields, but allow the impact of higher temperatures to vary for hotter versus colder districts. If farmers develop strategies when hot temperatures become common, a single hot day should be less harmful to crop yields in hotter districts than in colder districts. The difference between the impacts across the hotter versus colder districts is an estimate of adaptation.

I find four main results. First, higher temperatures are significantly harmful for agricultural yields across all districts. For example, relative to days in the 12-15°C range, having 10 additional days with daily temperature in the range of 27-30°C reduces agricultural yields by 9.3%. Second, evidence suggests that farmers in hotter districts effectively adapt to moderate ranges of heat. Specifically, the hotter districts have losses about 50% lower for temperatures ranging from 18-27°C than the colder districts. Third, temperatures over 30°C are equally harmful for both the hotter and colder districts, suggesting that adaptation to extremely high temperatures may be very difficult. Fourth, I find evidence of both intra-crop and inter-crop adaptations. Farmers in the hotter districts appear to be protecting themselves both by switching to crops that produce well under heat (inter-crop adaptation), as well as growing the same crops that cold regions grow, but using practices that more effectively protect the crop from heat (intra-crop adaptation).

This paper contributes to the rapidly growing literature on climate change adaptation, specifically in the area of agricultural adaptation (Fishman, 2012; Moore and Lobell, 2014; Taraz, 2015; Burke and Emerick, 2016). My work also relates to the strand of adaptation literature that uses the long-run frequency of events to estimate potential adaptation. Researchers have used this approach to study the relationship between temperature and numerous outcome variables, including economic growth (Dell et al., 2012), mortality (Barreca et al., 2015; Heutel et al., 2017), and labor.

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1 The range 12-15°C is equivalent to 53.6-59°F, and the range 27-30°C is equivalent to 80.6-86°F.
2 Hsiang (2016) provides a typology of adaptation models that supplies the term “time-series variation with stratification” to the approach this paper uses.
productivity (Park, 2016). My work also relates to the work on climate change impacts on Indian agriculture (Guiteras, 2009; Burgess et al., 2017).

This paper contributes to the literature in three respects. It provides the first set of estimates of the ability of farmers in India to adapt their crop agriculture to higher temperatures. Earlier work on agricultural adaptation in India has focused on adaptation to rainfall (Fishman, 2012; Taraz, 2015). In addition, this study is the first to use the long-run frequency approach to estimate agricultural adaptation in a developing country. Lastly, this paper provides crop-specific estimates of the impact of temperature on crop yields. Earlier work using the temperature binning approach in India has focused on the impact of heat on aggregate (rather than crop-specific) yields (Guiteras, 2009; Burgess et al., 2017).

This study has policy-relevant implications. The fact that farmers do not effectively adapt to extremely high temperatures suggests that providing direct aid to farmers in regions where extreme high temperatures become common should be a policy priority. More broadly, the persistent and substantial damages from high temperatures, even in areas that experience high temperatures frequently, underscores the need for adaptive development: development policies that emphasize risk mitigation and explicitly account for climate-change related risks, while continuing to promote growth, equity, and sustainability (Agrawal and Lemos, 2015).

The remainder of this paper is organized as follows. Section 2 gives background on Indian agriculture and agricultural adaptation. Section 3 describes the conceptual framework for the temperature binning approach. Section 4 describes the data sources used and presents summary statistics. Section 5 describes my strategy for estimating adaptation. Section 6 presents the results of the regressions. In Section 7, I discuss the implications of my findings. Section 8 discusses the policy implications of my results and directions for future research.
2 Background on Indian Agriculture and Agricultural Adaptation

Agriculture is the primary livelihood for India’s rural population, employing more than 50% of the rural workforce (India Ministry of Agriculture, 2015). Agriculture contributes roughly 12% of the gross domestic product (GDP) of the country’s economy (India Ministry of Agriculture, 2015). The percent contribution of agriculture to GDP is steadily declining as the country grows economically, but the fraction of the population reliant on agriculture remains high. The primary crops grown in India are rice and wheat, with sorghum, groundnut, maize, and sugarcane also being important. Indian farmers increasingly rely on irrigation, but as of 2010 only about 30% of all agricultural land was reliably irrigated (World Bank, 2017). The typical farm size is very small, with the average agricultural holding at about 1.3 hectares (Lowder et al., 2016). The primary \textit{kharif} growing season is June through September, and the secondary \textit{rabi} growing season is October through February (Krishna Kumar et al., 2004). Wheat is the main crop grown during the \textit{rabi} season.

The climate of India is diverse, but the majority of the country has a tropical climate (Pant and Kumar, 1997). The southern peninsular part of the country is hotter than the north, as displayed in Figure 1, which shows the average annual temperature for each district in India. Most of the rainfall occurs during the summer monsoon season, June through September (Pant and Kumar, 1997). Low rainfall is bad for crops, and high temperatures are also detrimental for crops (Guiteras, 2009).

Average temperatures in India have been increasing and are projected to increase further in the future. Farmers adjust their agricultural practices to adapt to increased temperatures in many ways. These potential adaptations include \textit{intra-crop} and \textit{inter-crop}.\footnote{Non-agricultural adaptations, such as seeking employment in other industries (Rose, 2001) and migration (Viswanathan and Kavi Kumar, 2015) fall outside of the scope of this study.} \textit{Intra-crop} adaptations occur when farmers grow the same crop (or crops) as before, but adjust their agricultural practices in order to make the crop more heat resistant. This includes investing in irrigation assets, since high heat can exacerbate drought, while irrigation can protect against drought. Farmers can shift sowing dates (Giné et al., 2009) to avoid the hottest time of year. Adjusting fertilizer and agricultural inputs...
to deal with heat are also intra-crop adaptations (Duflo et al., 2011). Farmers can grow the same basic type of crop (e.g., rice), but plant seed varieties that have been cultivated to be more heat resistant. Planting trees that provide protection from higher temperatures also constitutes intra-crop adaptation (FAO, 2017).

*Inter-crop* adaptation occurs when a farm shifts towards growing crops that produce more consistently in higher temperatures. Sorghum and maize are more heat tolerant than rice, for example. Switching to crops that are grown in the cooler part of the year, such as wheat, which is grown in the winter months in India, also constitutes inter-crop adaptation.

### 3 Conceptual Framework for Temperature Binning

To estimate the potential impacts of climate change on farmers, as well as to understand potential adaptation, it is necessary to accurately measure the impact of higher temperatures on crop yields. D’Agostino and Schlenker (2016) provide a helpful summary of studies that use weather fluctuations to analyze how climate change will affect agricultural yields.

One methodology is to look at how average temperature over the entire growing season affects agricultural output. To do this, researchers regress agricultural yields on average growing season temperature and estimate a coefficient that tells them how harmful higher temperatures are for crops. The limitation of this methodology is that averaging the temperatures over the entire growing season may obscure the effect of day-to-day variation. Therefore, some researchers prefer to use a finer-resolution analysis that incorporates day-to-day fluctuations in temperature (Schlenker and Roberts, 2009).

Researchers seeking a finer-resolution analysis have used daily temperature bins (Guiteras, 2009; Schlenker and Roberts, 2009; Burgess et al., 2017). This methodology looks at daily average temperature rather than growing season average temperature. The methodology works as follows. The researcher uses daily temperature data to construct variables that represent the num-

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4It is also possible to use cooling degree days and heating degree days to estimate the impact of temperature on yields. For a discussion of this approach, see D’Agostino and Schlenker (2016).
ber of days in the growing season that fell into certain temperature ranges, or bins. For example, if the typical range of temperatures for the study region ranged from 12°C to 30°C, and the researcher wanted to have 8 bins, the research could construct bins for less than 12°C, 12-15°C, 15-18°C, 18-21°C, 21-24°C, 24-27°C, 27-30°C, and greater than 30°C. Then the researcher runs a regression of the following form:

$$\ln(yield_{it}) = \sum_{j=1}^{n} \beta_j \text{temperature}_{ijt} + \alpha_i + \gamma_t + \epsilon_{it},$$

where $yield_{it}$ is the crop yield in location $i$ in year $t$ and $\text{temperature}_{ijt}$ represents the number of days in the $j$th bin in year $t$ in location $i$. The regression includes a location fixed effect $\alpha_i$ and year fixed effects $\gamma_t$ and an error term $\epsilon_{it}$. The location fixed effect controls for unobserved, time-invariant location-specific factors that may affect yields. The year fixed effect controls for unobserved shocks that may affect yields in a given year.\(^5\)

The temperature binning approach has several important aspects. First, because the total number of days always adds up to the same number (the length of the growing season) the researcher must exclude one bin from the regression, which becomes the reference bin. Second, the interpretation of the coefficients on the temperature bins is as follows. Suppose we are interested in the bin for 27-30°C and the reference bin is 12-15°C. Consider a year with a certain distribution of daily temperatures and suppose that a single day that had been 12-15°C was changed to 27-30°C. The coefficient on 27-30°C tells us how much yields would decrease, due to this change. Third, the choice of the number of bins, the width of the bins, and the range of the bins is up to the researcher. Narrower bins give more precision but require more data to estimate. Fourth, a key benefit of this methodology is its flexibility. The temperature binning approach does not assume greater heat has uniform effects regardless of magnitude. Thus, if moderate increases in temperatures benefit yields and extreme increases are detrimental, it can reveal this. Fifth, a key assumption of the temperature binning approach is that the impact of daily temperature is additive and separable over the growing season. In other words, it assumes that the marginal impact of a single day in 27-30°C on yields

\(^5\)Note that researchers typically use additional control variables, for example for precipitation. See Section 5 for a discussion of the control variables the current study uses.
is the same regardless of when the hot day occurs during the growing season, and regardless of whether the rest of the growing season has been very hot or very cold. Researchers have found that these assumptions are not too onerous in most cases (Schlenker and Roberts, 2009).

4 Data

4.1 Agricultural Data

I use agricultural data from the Village Dynamics in South Asia Meso data set (VDSA), which researchers at the International Crops Research Institute for the Semi-Arid Tropics compiled (ICRISAT, 2015). The data set provides information on annual agricultural production, prices, acreage, and yields, by crop, for 307 districts in 19 states over the period 1961–2011. Note that over this time period, some new districts were created. The VDSA data set assigns information about these “child” districts back to their “parent” district, so that the data set refers to geographic units that are constant over time. Because I am interested in studying the impact of higher temperatures on crops, I drop the states Assam, Himachal Pradesh, and Uttarakhand from my analysis because these states are significantly colder than the rest of India and do not experience very many hot days. The remaining sample consists of 286 districts.⁶

My outcome variable is agricultural yield for each district in each year, measured in rupees per hectare.⁷ Following Jayachandran (2006), Pande and Duflo (2007), and Guiteras (2009), I focus on the yields of the six major crops: rice, wheat, sorghum, groundnut, maize, and sugarcane. These crops have the highest revenues, and together account for more than 85% of total agricultural revenue over my sample period. Following Guiteras (2009) and Burgess et al. (2017), I focus on the impact of heat on agricultural yields, rather than agricultural revenues. This is because local heat shocks may affect local prices as well as yields, because agricultural markets in India are not well integrated. Price effects will increase farmers’ revenues and hence will partially offset their

⁶The mean daily temperature for the dropped states is 16°C, which falls below the 5th percentile of the distribution of daily temperature for the rest of the country.

⁷The year is defined as the agricultural year, which runs from July through June.
yield losses. But the higher agricultural prices will hurt the households that purchase the crops. Thus, to capture both losses to producer and consumer surplus, it makes more sense to look at agricultural yields (Cline, 1992). To create a composite crop yield measure that aggregates the top six crops, I use average district-level crop-specific prices from 1966 to 1970, which removes the effect of climate shocks on prices, an approach that Pande and Duflo (2007) and Guiteras (2009) used.

Table 1 presents the summary statistics for the agricultural and weather data sets. The first column pools all districts together, and the next two columns look separately at districts that are below or above the median of the long run of average district temperature. The aggregate yield and the crop-specific yield variables are roughly equal for the two groups. However, the colder districts grow a greater proportion of rice than the hotter districts and the hotter districts grow a greater proportion of wheat and sorghum than the colder districts.

4.2 Weather Data

I merge the agricultural data with rainfall and temperature data from the ERA-Interim Reanalysis archive, a gridded re-analysis weather data set. The data set provides information on the total precipitation, average temperature, maximum temperature, and minimum temperature over each 12-hour period on a 1 degree by 1 degree latitude-longitude grid, for the years 1979-2015 (Dee et al., 2011). This data set has been used to study agricultural outcomes in India previously by Colmer (2016). I use the daily weather data for each grid point to construct district-level daily weather outcomes, by calculating the weighted average of grid points within 100 kilometers of the district’s geographic center. I use the inverse square root of the distance from the district center as the weight. Figure 1 shows a map of the average annual temperature for each district in India, to give a sense of the spatial variation of temperature.

Although India has multiple growing seasons, I focus on June to December. This time range captures all of the kharif (main) growing season, as well as the part of the rabi season that includes
hot days.\footnote{January and February are part of the \textit{rabi} season, but hot days in those months are rare. Burgess et al. (2017) provides a precedent for limiting analysis to June–December for this reason.}

Figure 2 shows the distribution of daily average temperature for districts that are hotter than, or colder than, the median district. As the figure shows, both the hotter and the colder districts do experience very hot days, but the hotter districts experience them more frequently. The hotter districts have 48 days with daily average temperature ranging 27-30°C and 25 days with daily temperature over 30°C each year, whereas the colder districts experience 23 days in the 27-30°C range and only 11 days in the greater than 30°C bin.

## 5 Analysis

### 5.1 Baseline Specification

I begin by estimating the impact of temperatures on yields. Following Burgess et al. (2017), I estimate:

\[
\ln(yield_{it}) = \sum_{j=1}^{8} \beta_j temperature_{ijt} + \sum_{k=1}^{3} \delta_k rain_{ikt} + \alpha_i + \gamma_t + \lambda_1 t + \lambda_2 t^2 + \epsilon_{it},
\]  

where \( yield_{it} \) is the agricultural yield per acre for district \( i \) in year \( t \). The variable \( yield_{it} \) is an aggregate yield, equal to the total value of the top six crops grown (rice, wheat, sorghum, groundnut, maize, sugarcane) divided by the total area planted with those crops, using base year prices from 1966 to 1970. The variables \( temperature_{ijt} \) are binned temperature variables that represent the number of days that fall into each of eight temperature bins. The lowest temperature bin captures days with daily average temperature less than or equal to 12°C. The highest temperature bin captures days with daily average temperatures greater than or equal to 30°C. The remaining temperature bins are 3-degree wide bins between these two end points: 12-15°C, 15-18°C, and so on, up to 27-30°C.

The temperature bin values are calculated based on days during the months of June through January and February are part of the \textit{rabi} season, but hot days in those months are rare. Burgess et al. (2017) provides a precedent for limiting analysis to June–December for this reason.
December, in order to capture the core growing season months. Since there are a fixed number of
days that occur from June to December each year, the temperature bins always add up to the same
quantity, and hence a regression that included all eight temperature bins would not be uniquely
identified. To address this, I treat the bin 12-15°C as the omitted category. The interpretation of
each $\beta_j$ is that it represents the impact on yields of having one more day in the year in bin $j$, relative
to the impact of a day in the 12-15°C range.

The variable $\text{rain}_{ikt}$ is an indicator variable for whether rainfall for district $i$ in year $t$ falls in
tercile $k$ of the long-run rainfall distribution for that district. The middle tercile ($k = 2$) is the
omitted category. This specification allows for nonlinear rainfall effects. The regression includes
a district fixed effect $\alpha_i$, year fixed effects $\gamma_t$, region-specific quadratic time trends $\lambda_1^r t$ and $\lambda_2^r t^2$
and an error term $\epsilon_{jt}$. The district fixed effect controls for unobserved, time-invariant, district-level
factors that may affect yields, such as soil quality. The year fixed effects allow me to control for
unobserved shocks, such as trade shocks, that may affect yields in all districts in a given year. The
region-specific quadratic trends allow me to control for smoothly varying regional effects, such as
agricultural technology, that may be changing and affecting yields over time.

I am interested in the marginal effect of an additional hot day on yields, and so the coefficients
of interest are the $\beta_j$’s. I expect to find that $\beta_j < 0$ for large values of $j$. In other words, I expect
to find that higher temperatures lead to reductions in agricultural yields. I also expect that the
magnitudes of the $\beta_j$ coefficients should increase as $j$ gets larger. In other words, heat-induced
losses are larger for higher levels of heat.

5.2 Test for Adaptation

After running my baseline temperature-yield regression, I run an alternate specification that allows
the coefficients on the temperature bins to vary depending on whether a particular district is hotter
or colder than the average district. Specifically, I calculate the long-run average temperature (based
on the months June through December) for each district, based on the years 1979–2011. I calculate
the median value for long-run average temperature amongst all the districts, and then I create a
dummy variable $hot\_district_j$ that is equal to 1 if a given district’s long-run average temperature is above the median value, and is equal to zero otherwise. Then I run a regression of the form:

\[
\ln(yield_{it}) = \sum_{j=1}^{8} \beta_j^H temperature_{ijt} \times hot\_district_j + \\
\sum_{j=1}^{8} \beta_j^C temperature_{ijt} \times (1 - hot\_district_j) + \\
\sum_{k=1}^{3} \delta_k rain_{ikt} + \alpha_i + \gamma_t + \lambda_1^t + \lambda_2^t t + \lambda_3^t t^2 + \epsilon_{it}.
\] (2)

As with my baseline regression, I am interested in the marginal effect of additional hot days on yields. The coefficients of interest are $\beta_j^H$ and $\beta_j^C$. The coefficients $\beta_j^H$ capture the impact of temperature on yields in hotter districts, and the coefficients $\beta_j^C$ capture the impact of temperature on yields in colder districts. As before, I expect that higher temperatures are bad for yields, and that this effect intensifies as temperatures get higher. So I expect $\beta_j^H < 0$ and $\beta_j^C < 0$ for large values of $j$. I also expect that the magnitudes of $\beta_j^H$ and $\beta_j^C$ increase as $j$ gets larger.

In addition, I expect that hotter temperatures are more harmful for the colder districts, because farmers in these districts experience high heat less frequently, and as a result may not be as well adapted to it. Conversely, I expect that the losses from high temperatures will be lower in places that experience high temperature more frequently. So, I expect that $\beta_j^C < \beta_j^H$.

Furthermore, I can use the estimates of $\beta_j^H$ and $\beta_j^C$ to construct a measure of adaptation. If $\beta_j^H$ is less than $\beta_j^C$, then the value $(\beta_j^C - \beta_j^H) / \beta_j^C$, or equivalently, $1 - \beta_j^H / \beta_j^C$, represents the fraction of the bin $j$ temperature losses in colder districts that have been adapted away in hotter districts.

5.3 Crop-Specific Regressions

After running the baseline regressions and the test for adaptation using the composite yield measure that aggregates the top six crops, I also run these regressions for the individual crops, separately. Again, I am interested in the coefficients on the temperature bins, and in the relative size of the coefficients for the hotter versus the colder districts. As with the aggregate crop yield measure, I
expect that $\beta_j^C < \beta_j^H$.

As before, the value $1 - \beta_j^H / \beta_j^C$ represents a measure of adaptation. I expect that the percentage value of adaptation will be smaller for the individual crop yield regressions than for the aggregate crop yield regression. When looking at the aggregate crop measure, the hotter districts can adapt in two ways. They can shift towards crops that are less sensitive to heat, and they can grow the same crops as before, but grow them in ways that minimize their heat losses. I refer to the first method as inter-crop adaptation, and the second method as intra-crop adaptation. When looking at aggregate yields, and comparing heat impacts across the hotter versus colder districts, I will be measuring the effect of both inter- and intra-crop adaptation. When I look at individual crop yield regressions, any adaptation that I measure will be intra-crop adaptation.

6 Results

6.1 Baseline Results

Figure 3 plots the temperature bin regression coefficients from estimating equation 1 for aggregate yields. The temperature bin 12-15°C was chosen to be the omitted reference bin because the literature suggests that this temperature range is most beneficial for crops. In line with this expectation, the graph demonstrates that crop yield was highest when daily average temperatures were in the 12-15°C range and yield decreased if daily average temperatures exceeded 15°C. Furthermore, the damages from higher temperatures increase as the temperatures increase, with roughly a linear relationship.\(^9\) In terms of magnitudes, the coefficient on the 27-30°C bin is -0.00929, which implies that, on average, having 10 more growing season days with average temperature in the 27-30°C range reduces yields by 9.3%, compared to if those days had been in the 12-15°C reference bin.

\(^9\)Colder temperatures in the range below 12°C also have a negative impact on crop yields, but the magnitude of this effect is small. In addition, there were not many days with daily average temperature in this bin.
6.2 Adaptation Results: Aggregate Yields

Figure 4 plots the temperature bin coefficients from regression 2, which allows the impact of temperatures on yields to vary across districts that experience high temperatures more or less frequently. The blue line represents the districts that are colder than the median district and the red line represents the districts that are hotter than the median district.

The graph illuminates the answers to the research questions in several ways. First, high temperatures are more harmful in colder districts, as demonstrated by the fact that the coefficients are more negative for the blue line. Second, hotter districts are harmed by high temperatures, if not as much as cooler districts. For the hotter districts, the slightly warmer bin, 15-18°C, appears to be beneficial for crop yields, but the coefficients for the bins above 18°C remain negative. Third, the fraction of adaptation is diminishing as temperatures increase. We see that at lower temperatures, the hot districts have adapted away all of the negative impacts of higher heat. For moderately high temperatures, the hot districts have eliminated about 40–50% of the losses that cold districts experience through adaptation. None have adapted to temperatures over 30°C, which suggests adaptation may not be possible, or may be very difficult. The losses from this bin are the same for both hot and cold districts, demonstrating that the hot districts have not been able to adapt away the negative impacts of extreme temperatures. Figure 9 presents the fraction of adaptation, at different temperature bins, by graphing the value $1 - \beta_j^H / \beta_j^C$.

In terms of magnitudes, having 10 more days in bin 27-30°C, reduces yields by 10.4% for the colder districts, but only by 7.3% for the hotter districts, demonstrating that 30% of the losses have been adapted away for that temperature bin in the hotter districts. In terms of statistical significance, the temperature bin coefficients are statistically significantly different for the hotter and colder districts for bins 15-18°C and 18-21°C at the 10% level, and statistically significantly different at the 5% level for bins 21-24°C, 24-27°C, and 27-30°C.
6.3 Adaptation Results: Crop-Specific Yields

Figures 5-8 present the temperature bin coefficients from estimating equation 2 for rice, wheat, and sorghum, separately.

Figure 5 presents the results for rice yields. The graph looks very similar to the graph for aggregate yields, with the losses for the colder districts exceeding the losses for the hotter districts.\(^{(10)}\) But rice yields differ from aggregate yields in one important way: the magnitude of the coefficients is larger than for the aggregate yields. In other words, rice yields are more sensitive to losses due to heat than the aggregate crop yield measure. Specifically, 10 more days in the 27-30\(^\circ\)C bin would reduce rice yields by 19\% and 11\% for the colder and hotter districts respectively, compared to losses of 10\% and 7\% respectively in aggregate crops.

We can also compare the hotter and colder district coefficients to estimate adaptation: the fraction of heat losses for each bin that the red districts have been able to adapt away. The yellow line on Figure 9 plots the quantity \(1 - \frac{\beta_j^H}{\beta_j^C}\) for the rice yields. We can see that the fraction of adaptation is similar for rice as it was for aggregate yields: starting at close to 100\% (all the negative heat impacts are adapted away for moderate levels of heat) and falling to be close to zero (at very high levels of heat, adaptation does not appear to be possible).

Figure 6 presents the results for wheat. As with the composite yields and rice yields, high temperatures are more damaging for the colder districts and less damaging for the hotter districts, which indicates evidence of adaptation. However, the graph suggests wheat farmers can adapt more easily than rice farmers or the aggregate. Bins 18-21\(^\circ\)C and 21-24\(^\circ\)C are not damaging for wheat yields for the hotter districts, whereas they are for the colder districts. Furthermore, even at higher temperatures, the damages in the hotter districts remain substantially smaller than the colder district damages. The green line in Figure 9, which plots the quantity \(1 - \frac{\beta_j^H}{\beta_j^C}\) for the wheat yields, shows this comparison. For moderate ranges of heat, farmers in hot districts have adapted to the point where they have eliminated almost all of the damages, and they have adapted a larger

\(^{(10)}\)The difference in the magnitudes of the coefficients across hot and cold districts is statistically significant at the 10\% level for bin 5, and the 5\% level for bins 3, 4, 6, and 7.
fraction of damages at the highest bin than aggregate yields and rice yields reflect.

In terms of magnitudes, 10 more days in the 27-30°C bin reduces yields by 5% for the hotter districts and by 8% for the colder districts. The difference in impacts across the hotter and colder districts is statistically significant at the 10% level for bin 4 and the 5% level for bins 5, 6, 7, and 8.

The results of the regression related to wheat have an important caveat, however. In keeping with the other figures, the regression specifications for Figure 6 uses all days from the months of June through December. But wheat is typically grown in the *rabi* season, which begins in October. Thus the regression includes June-September temperatures prior to the planting of wheat. Yet, hot days during the *kharif* seasons can still affect wheat yields in the *rabi* season, via soil moisture, surface water supplies, and groundwater supplies (Zaveri et al., 2016).

Nevertheless, for completeness, I re-ran my wheat yields regression using an alternate specification where I restrict the analysis to days that fall within the *rabi* season (October-December). Figure 7 presents the results of this regression. The pattern of the figure is broadly the same as for the initial wheat figure: losses are smaller in the hotter districts than in the colder districts. This figure drops the top bin (>30°C), because there are too few days during October-December in that temperature range for it to be identified.

Figure 8 presents the results for sorghum. Interestingly, the hotter and colder districts did not significantly differ for this crop in their magnitudes of temperature-induced yield losses. This suggests sorghum farmers are not doing anything different in the hotter districts to adapt, unlike rice and wheat farmers (or that any measures they take are ineffective in boosting crop yields).

Figures A1, A2, and A3 in Appendix A presents the corresponding graphs for sugarcane, maize, and groundnut. The sugarcane graph resembles that of rice and wheat in that losses in hotter districts are less than losses in colder districts. For maize, we see a similar graph as for sorghum, where there is no statistically significant difference between the heat-induced losses across the hotter and the colder districts. For groundnut, we see an unexpected pattern, which is that heat losses are actually larger for hotter districts, which is the opposite of what we would expect if farmers
were adapting to heat. However, an important caveat for these crops is that many districts grow a very small area of these crops, which may affect the quality of the yield data. If I drop districts that grow less than 2% of their area with groundnut from my regression, then the unexpected result goes away, suggesting that it is just due to a quirk in the data. Therefore, I interpret my data to be inconclusive as to whether groundnut farmers have adapted to the heat. Similarly, for sugarcane, if I drop districts that grow less than 2% of their area with sugarcane, then I no longer find a statistically significant difference between the hot and cold districts. Importantly, my core results for rice, wheat, and sorghum are unchanged if I drop districts that grow less than 2% area with the crop over my sample period, demonstrating that districts that grow very little of the crop analyzed have not driven those results.

7 Discussion

My results show that yield losses due to moderately high temperatures are different across the hotter and colder districts. Because the losses are smaller for districts that are hotter, I consider my results to be evidence of adaptation. Farmers in the hotter districts are doing something differently in their crop practices, which protects their crops, at least partially, from moderate levels of heat. While the data do not reveal which intra-crop adaptations farmers undertake, the study captures the impact of all adaptations farmers employ. However, the results do reveal the results of inter-crop adaptation. At the same time, results suggest that adaptation has not prevented impacts of the highest temperatures.

This study has some limitations. First, I have been assuming that all the differences in crop impacts, across the hotter and the colder districts, are due to adaptation. However, the hotter and colder districts may differ in other ways besides their average temperature. Importantly, my crop regressions include district fixed effects to control for unobserved location-specific factors that influence the level of crop yields. So, for example, if the hotter districts have better quality soil on average, which leads to higher yields, the district fixed effect will control for that factor and it will
not influence my adaptation estimates. On the other hand, if the hotter districts have better soil, and that makes the yields less sensitive to heat, my analysis will not control for that unobserved heterogeneity. Other work that uses the long-run frequency approach to estimating adaptation faces this concern as well (Hsiang, 2016).

A separate concern relates to temperature-induced migration and unobserved farmer ability. Extensive literature has addressed how climate change and environmental stressors affect migration (Bohra-Mishra et al., 2014; Dallmann and Millock, 2016; Koubi et al., 2016). The most relevant study is Bohra-Mishra et al. (2014), which looks at temperature-induced migration. The authors find that temperatures over 25°C can lead to outmigration. Of course, migration might not occur in the districts I consider, in which case the district fixed effects control for unobserved farmer ability, which is constant for each district, prevents any bias in the result from selection or unobserved farmer ability. On the other hand, if people migrate in response to climate, Bohra-Mishra et al. (2014) suggest it would occur from the hot regions to the colder regions. Other work has found that richer farmers are more likely to migrate in response to environmental shocks (Fishman, 2015). If these richer farmers tend to have higher farming ability, then the remaining, non-migrating farmers would have lower farming ability. Heat losses would appear to be larger in the hotter districts, but lower yields would actually reflect low levels of farming ability. However, my results show that heat losses are lower in the hotter districts. This suggests that migration is not driving the study results.

8 Conclusion

In India’s current climate, very hot days occur at extremely different rates in different districts. But climate change research suggests the number of very hot days will increase in all parts of India. By looking at the districts that currently experience heat frequently, we can get a sense of how feasible it is to adapt to extreme heat. This study finds substantial negative impacts of hot days on crop yields. Hotter districts have adapted to moderate levels of higher temperatures through both
inter-crop and intra-crop adaptation, but have not adapted to extreme levels of heat.

This study suggests many fruitful avenues for future research, most of which would depend on farmer-level data. First of all, the current study focuses on mean crop yields, and focuses on the mean level of farmer adaptation. However, crop yields vary substantially across individual farmers (Barnwal and Kotani, 2013). A farmer-level quantile analysis could analyze how higher temperatures affect the entire distribution of crop yields (not just the means), and how the entire distribution of farmers (not just the average farmer) adapt to higher temperatures. Second, it would be interesting to use farmer-level data to determine whether the farmers in hotter districts tend to grow a greater number of crops, and the role of crop diversification as an adaptation strategy (Chavas and Di Falco, 2011). A district-level analysis cannot analyze the number of different crops each individual farmer is growing. Thirdly, district-level analysis cannot determine the differential ability to adapt between different socioeconomic groups. Climate change may affect poor and marginalized groups, especially women (Esplen and Demetriades, 2009; Bhattarai et al., 2015; Van Aelst and Holvoet, 2016), and groups with low levels of human and social capital (O’Brien et al., 2004; Below et al., 2012) more than their counterparts. Future work with farmer-level data should test for differences in adaptive ability across socio-economic groups.

More broadly, there are many strategies for livelihood adaptation (Agrawal and Perrin, 2009), but my analysis captures only adaptations that relate to crop agriculture and that affect crop yields. I do not capture, for example, adaptations such as migration (Viswanathan and Kavi Kumar, 2015), or diversification outside of agriculture (Rose, 2001). Future work could apply a similar long-run frequency approach, as used in this study, to look at a broad set of non-agricultural adaptations.

Taken as a whole, the results of this study highlight the difficulty of private, individual adaptation to high temperatures. This points to the necessity of public policies focused on both development and adaptation, to allow for continued development in the presence of these now unavoidable climate shocks. Pro-poor programs in India, such as the Mahatma Gandhi National Rural Employment Gurantee Act (MGNREGA) have been shown to be effective in protecting households from climate shocks that affect other outcomes such as human capital (Garg et al., 2017). Future work
should examine the extent to which public policies can support agricultural adaptation to climate change.

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Figures

Figure 1: Average Annual Temperature by District
Figure 2: Distribution of Daily Average Temperature for Hotter and Colder Districts

Note: This figure displays the number of days in eight daily average temperature bins, focusing on days between June and December. The blue bars show the distribution of daily temperature for districts whose long-run district average temperature is below the median and the red bars show the distribution for above-median districts. Source: The temperature data are from the ERA-Interim dataset (1979–2011). The figure is constructed based on the author’s calculations.
Figure 3: The Effect of Daily Average Temperatures on Log Aggregate Yields

The circle markers represent the coefficient estimates of the effect on log aggregate yields of a day in a given temperature bin, relative to the effect of a day in the 12-15°C bin. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.
Figure 4: The Effect of Daily Average Temperatures on Log Aggregate Yields

The circle markers represent the coefficient estimates of the effect on log aggregate yields of a day in a given temperature bin, relative to the effect of a day in the 12-15°C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.
Figure 5: The Effect of Daily Average Temperatures on Log Rice Yields

The circle markers represent the coefficient estimates of the effect on log rice yields of a day in a given temperature bin, relative to the effect of a day in the 12-15°C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.
Figure 6: The Effect of Daily Average Temperatures on Log Wheat Yields

The circle markers represent the coefficient estimates of the effect on log wheat yields of a day in a given temperature bin, relative to the effect of a day in the 12-15°C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.
Figure 7: The Effect of Daily Average Temperatures on Log Wheat Yields, *Rabi* Months Only

The circle markers represent the coefficient estimates of the effect on log aggregate yields of a day in a given temperature bin, relative to the effect of a day in the 12-15°C bin. The days are restricted to those that fall within October to December. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.
The circle markers represent the coefficient estimates of the effect on log sorghum yields of a day in a given temperature bin, relative to the effect of a day in the 12-15°C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.
Figure 9: Fraction of Adaptation

The figure displays the fraction of heat losses that have been adapted away in the hotter districts, relative to the level of heat losses in the colder districts.


**Tables**

**Table 1: Summary Statistics**

<table>
<thead>
<tr>
<th></th>
<th>Full Sample</th>
<th>Colder Districts</th>
<th>Hotter Districts</th>
</tr>
</thead>
<tbody>
<tr>
<td>Log aggregate yield of top six crops (Rs./hectare)</td>
<td>7.429</td>
<td>7.431</td>
<td>7.426</td>
</tr>
<tr>
<td></td>
<td>(0.563)</td>
<td>(0.545)</td>
<td>(0.580)</td>
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<td>Log rice yield (Rs./hectare)</td>
<td>7.359</td>
<td>7.347</td>
<td>7.371</td>
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<tr>
<td></td>
<td>(0.637)</td>
<td>(0.622)</td>
<td>(0.654)</td>
</tr>
<tr>
<td>Log wheat yield (Rs./hectare)</td>
<td>7.370</td>
<td>7.290</td>
<td>7.456</td>
</tr>
<tr>
<td></td>
<td>(0.537)</td>
<td>(0.526)</td>
<td>(0.535)</td>
</tr>
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<td>Log sorghum yield (Rs./hectare)</td>
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<td>6.288</td>
<td>6.013</td>
</tr>
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<td></td>
<td>(0.653)</td>
<td>(0.430)</td>
<td>(0.763)</td>
</tr>
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<td>Log groundnut yield (Rs./hectare)</td>
<td>7.053</td>
<td>7.045</td>
<td>7.059</td>
</tr>
<tr>
<td></td>
<td>(0.482)</td>
<td>(0.407)</td>
<td>(0.536)</td>
</tr>
<tr>
<td>Log maize yield (Rs./hectare)</td>
<td>6.812</td>
<td>6.847</td>
<td>6.773</td>
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<td>(0.583)</td>
<td>(0.543)</td>
<td>(0.622)</td>
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<td>Log sugarcane yield (Rs./hectare)</td>
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<td>(0.703)</td>
<td>(0.793)</td>
<td>(0.585)</td>
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<td>Fraction of top six crop area planted with rice</td>
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<td>(0.345)</td>
<td>(0.323)</td>
<td>(0.343)</td>
</tr>
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<td>Fraction of top six crop area planted with wheat</td>
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<td>0.317</td>
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<tr>
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<td>(0.287)</td>
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<td>(0.316)</td>
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<tr>
<td>Fraction of top six crop area planted with sorghum</td>
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<td>0.0943</td>
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<td>(0.213)</td>
<td>(0.196)</td>
<td>(0.223)</td>
</tr>
<tr>
<td>Fraction of top six crop area planted with groundnut</td>
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</tr>
<tr>
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<td>(0.163)</td>
<td>(0.129)</td>
<td>(0.187)</td>
</tr>
<tr>
<td>Fraction of top six crop area planted with maize</td>
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<td>0.0593</td>
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<tr>
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<td>(0.119)</td>
<td>(0.0853)</td>
<td>(0.144)</td>
</tr>
<tr>
<td>Fraction of top six crop area planted with sugarcane</td>
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<td>0.0432</td>
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</tr>
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<td>Observations</td>
<td>9278</td>
<td>4658</td>
<td>4620</td>
</tr>
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</table>

Mean coefficients, standard deviation in parentheses.
A Appendix Tables and Figures
Figures

(a) Colder and Hotter Districts Separately

Figure A1: The Effect of Daily Average Temperatures on Log Sugarcane Yields

The circle markers represent the coefficient estimates of the effect on log sugarcane yields of a day in a given temperature bin, relative to the effect of a day in the 12-15°C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.
Figure A2: The Effect of Daily Average Temperatures on Log Maize Yields

The circle markers represent the coefficient estimates of the effect on log maize yields of a day in a given temperature bin, relative to the effect of a day in the 12-15°C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.
(a) Colder and Hotter Districts Separately

Figure A3: The Effect of Daily Average Temperatures on Log Groundnut Yields

The circle markers represent the coefficient estimates of the effect on log groundnut yields of a day in a given temperature bin, relative to the effect of a day in the 12-15°C bin. The blue markers represent the colder districts and the red markers represent the hotter districts. The dashed lines represent the 95% confidence interval of the estimates. Standard errors clustered at the district level. See Section 5 for more details on the methodology used to estimate these coefficients.
Table A1: Impact of Temperature on Crop Yields, For Hotter and Colder Districts

<table>
<thead>
<tr>
<th>Bin 1 (colder districts)</th>
<th>Aggregate</th>
<th>Rice</th>
<th>Wheat</th>
<th>Sugar</th>
<th>Groundnut</th>
<th>Sorghum</th>
<th>Maize</th>
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<td>-0.000928</td>
<td>-0.00361***</td>
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<td>0.00110</td>
<td>-0.00800**</td>
<td>-0.000733</td>
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<td>(0.00167)</td>
<td>(0.00144)</td>
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<tr>
<td>Bin 1 (hotter districts)</td>
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<td>-0.00240</td>
<td>0.000151</td>
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<td>-0.0170***</td>
<td>0.00991***</td>
<td>0.00342**</td>
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<td>(0.00107)</td>
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<td>(0.00163)</td>
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<td>Bin 3 (colder districts)</td>
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<td>(0.00216)</td>
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<td>(0.00125)</td>
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<tr>
<td>Bin 4 (colder districts)</td>
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<td>(0.00125)</td>
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<td>-0.0128***</td>
<td>-0.00629***</td>
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<td>(0.00229)</td>
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<td>-0.00650**</td>
<td>-0.00345***</td>
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<td>(0.00144)</td>
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Observations: 9278 8681 7910 7145 7541 8142 8085
R^2: 0.488 0.375 0.386 0.220 0.231 0.311 0.142
Adjusted R^2: 0.485 0.371 0.381 0.214 0.225 0.306 0.136

Standard errors in parentheses
* p < 0.10, ** p < 0.05, *** p < 0.01
### Table A2: Impact of Temperature on Crop Yields, Difference Across Hotter and Colder Districts

<table>
<thead>
<tr>
<th>Bin 1 (all districts)</th>
<th>Aggregate</th>
<th>Rice</th>
<th>Wheat</th>
<th>Sugar</th>
<th>Groundnut</th>
<th>Sorghum</th>
<th>Maize</th>
</tr>
</thead>
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<td>(2)</td>
<td>(3)</td>
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<td>(5)</td>
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Observations 9278 8681 7910 7145 7541 8142 8085

| R²          | 0.488 | 0.375 | 0.386 | 0.220 | 0.231 | 0.311 | 0.142 |
| Adjusted R² | 0.485 | 0.371 | 0.381 | 0.214 | 0.225 | 0.306 | 0.136 |

Standard errors in parentheses
*p < 0.10, **p < 0.05, ***p < 0.01