How Do Droughts Impact Household Food Consumption and Nutritional Intake? A Study of Rural India

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Abstract

This paper investigates the impacts of droughts on food expenditure and macronutrient consumption among rural Indian households. To isolate causal effects, I exploit random year-to-year variation in a dry shock, defined as the absolute deviation of rainfall below its long-run mean. I find that the dry shock has a statistically significant and negative effect on household nutrition. For a median dry shock, I estimate that households spend 1 percent less per capita per month on food and consume up to 1.4 percent fewer calories, protein, and fat. Disaggregating the effects by food group, I demonstrate that household diets become less balanced as a result of droughts: the dry shock leads households to rely primarily on cereals and to purchase less vegetables, fruits, pulses, and animal-sourced foods. Hence, droughts negatively impact not only the quantity but also the quality of rural household diets. Finally, I explore the potential channels for these effects. I argue that rather than higher food prices, a decline in household market and non-market income is the primary reason for lower household food consumption and nutrition during droughts. Taken together, these findings suggest that attaining food security amid extreme weather conditions requires an integrated approach that focuses on food not only for survival but also for leading a healthy and active life.

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1. Introduction

Achieving food security and improved nutrition—the second of the United Nations' Sustainable Development Goals by 2030—persists as one of the most pressing development challenges in the world today. Estimates suggest that, in 2013, almost 850 million people still experienced chronic hunger, and the most vulnerable lacked adequate nourishment for normal physical development (FAO, IFAD, & WFP, 2013). Simultaneously, the changing climate looms large over the ongoing fight to end hunger: the frequency, intensity, and duration of droughts are expected to increase worldwide in the coming years, threatening global and local food systems.[1] Hence, to develop effective policies for mitigating the effects of climate change in the future, it is critical to understand the effects of drought upon food security along multiple dimensions: food availability (e.g., agricultural production), food access (e.g., the affordability of food), and food utilization (e.g., the quality of household diets).

This paper sheds light on food utilization and household nutrition in the face of droughts. A vast body of research has already established that inadequate precipitation significantly reduces crop yields and agricultural productivity (IPCC, 2014). Conventional intuition suggests this lower food availability would translate into poorer food utilization; however, it is not immediately clear that such a harmful consequence may materialize because a combination of trade, storage, or savings may offset the negative impacts of a dry rainfall shock. The magnitudes of effects on food utilization also remain relatively understudied, and our knowledge about the mechanisms of impact is particularly limited. To fill these gaps in the literature, my empirical analysis focuses on two research questions: How do dry rainfall shocks influence rural household food expenditures, the quality of their diet, and their macronutrient intake? And what role do prices and income play as channels for these impacts?

I examine the above issues in the context of rural India, an environment home to 80 percent of the country's poor and where precipitation has important consequences for food security, as agriculture continues to be primarily rain-fed (World Bank, 2016; Ministry of Agriculture, 2017). Rural India offers a useful empirical setting not only because the vast majority (i.e., 60 percent) of households earn income from agriculture (NSS, 2014a) but also due to the tremendous variability of rainfall patterns across time and space.[2] Moreover, remarkably rich microdata on rural household food expenditure are available through India's National Sample Survey (NSS) Consumer Expenditure modules, which contain market purchases, home production, and in-kind transfers for over 300 food items. With an exhaustive picture of household food consumption, these data therefore allow me to construct measures of household nutrition, particularly per capita caloric, protein, and fat intake.

Since several prior studies have suggested that more rainfall tends to be beneficial in India (e.g., Jayachandran, 2006; Duflo & Pande, 2007), food security becomes a more relevant concern during droughts. Thus, throughout this paper, I concentrate on the effects of a *dry shock*, defined as the absolute deviation of rainfall, in meters per year, below the district's long-run mean. My empirical strategy then takes advantage of exogenous variation in the dry shock across years in a given district. To the extent that variation in weather shocks is plausibly random over time, this approach enables me to capture the causal effect of low rainfall on food utilization. My results show that droughts have a statistically significant and negative effect on household food consumption and nutrition. Droughts therefore bring households all the more below recommended dietary allowances for healthy nutrition, as the typical rural individual obtains very low or minimal levels of energy and macronutrients to begin with. Yet, the magnitudes of impact are quite small. I find that during a median dry shock, corresponding to total annual rainfall that is 0.15 meters below the long-term average, households spend 1 percent less on food. They also consume 0.7 percent fewer calories, 0.8 percent fewer milligrams of protein, and 1.4 percent fewer milligrams of fat. Importantly, these estimates hold up to a battery of robustness checks, including alternative control variables, dry shock definitions and specifications, regression error structures, and functional forms.

To probe into how patterns of food intake change with the dry shock, I disaggregate impacts into six food groups: cereals; pulses; vegetables and fruits; animal-sourced products; sugars, oils, and fats; and processed foods. This analysis is especially beneficial for policy, as it indicates where dietary deficiencies may be during droughts. Notably, the disaggregated results show negative effects of the dry shock across the board. The largest nutritional impacts in percentage terms are evident for processed foods, where a median dry shock results in 3 to 5 percent less consumption of calories, protein, and fat. At the other extreme, the smallest nutrition effects are seen for cereals, for which the same dry shock causes only 0.2 to 0.4 percent less macronutrient intake. A median dry shock likewise induces households to forgo products that impart palatability (e.g., cooking fats) and to consume less naturally nutrient-rich foods (e.g., vegetables), as spending on these items decrease by 1 to 2 percent.

In addition to establishing that droughts have a statistically significant negative effect on food consumption and nutrition, I investigate food prices and income as potential channels for these impacts. My analysis reveals two interesting insights. First, for all food items I consider, I am unable to reject the hypothesis that the dry shock has a null effect on prices—a finding that is robust to different subsamples and sources of price data. These results echo Zimmermann (2017) and Blakeslee and Fishman (2018), who have argued that storage and transport infrastructure have made food prices less sensitive to rainfall in India. Second, droughts statistically significantly and negatively impact employment and earnings. In particular, the dry shock increases unemployment and decreases employment by similar magnitudes, with no effects on labor force participation. The lower employment rates during droughts are likewise accompanied by decreased average daily earnings, measured among casual and salaried workers in the agricultural and non-agricultural sectors. Taken together, these results suggest that the adverse implications of a dry shock on household food security likely operate by way of impacting livelihoods rather than prices. My findings therefore relate to the seminal work by Sen (1981), as I show that income and livelihoods have important ramifications for hunger and nutrition.

This paper contributes to the literature and policy discourse concerning food security and weather shocks. Existing research on this topic remains highly skewed: of peer-reviewed journal articles on food security and climate variability since 1990, 70 percent analyze food availability but only 13.9 percent investigate food utilization (Wheeler & von Braun, 2013). By focusing on the impact of dry shocks on household diet and nutrition—issues that encompass food utilization—this paper expands the existing knowledgebase about food security during droughts. Overall, I find that low rainfall reduces not only the quantity of food households consume but likewise the nutritive value, balance, and quality of their diet. Consequently, attaining food and nutrition security in extreme weather conditions requires an integrated approach that focuses both on food for survival and for leading a healthy and active life. I believe these insights may aid Indian policy makers in adapting the country's existing nutrition-related programs (e.g., National Food Security Act, Mid-Day Meal Scheme) for the future, especially in light of growing concerns regarding food security amid a changing climate.

2. Background and literature review

Food utilization is one pillar of food security, a complex and multifaceted concept.

Although many interpretations of the term *food security* exist, in this paper I adopt the widely used definition proposed by the FAO (see FAO, IFAD, & WFP, 2013, p. 50):

> **Food security.** A situation that exists when all people, at all times, have physical, social and economic access to sufficient, safe and nutritious food that meets their dietary needs and food preferences for an active and healthy life.
>
> **Food insecurity.** A situation that exists when people lack secure access to sufficient amounts of safe and nutritious food for normal growth and development and an active and healthy life. It may be caused by the unavailability of food, insufficient purchasing power, inappropriate distribution or inadequate use of food at the household level.

The above characterization highlights four dimensions of food (in)security: (1) *availability*, as determined by food production, stock levels, net trade, and food aid; (2) *access*, referring to economic, social, and physical factors such as income, purchasing power, and market infrastructure; (3) *utilization*, involving diet quality, diet diversity, and the nutritional aspects of food consumption; and (4) *stability*, the ability of individuals, households, and communities to cope with negative shocks, for example, due to low levels of precipitation.

A very large literature ranging from the physical to the social sciences has investigated the impacts of droughts on food availability. While these studies cannot be adequately summarized here, the broad-scale adverse effects of low rainfall on crop production are generally well understood. Droughts cause significant reductions in yield across agricultural systems in many contexts, though these effects may be partially attenuated using irrigation, water storage, and agricultural technologies (IPCC, 2014; Dell et al., 2014; Knox et al., 2012; Carleton & Hsiang, 2016). In India, as with many other developing countries, multiple analyses of the weather–agriculture relationship likewise find consistent negative impacts of extreme weather conditions not only on agricultural outputs but also on rural incomes (e.g., Auffhammer, Ramanathan, & Vincent, 2012; Jayachandran, 2016; Mahajan, 2017; Taraz, 2018).

Despite this vast research concerning food production, much less is known about how dry rainfall shocks influence food utilization. In an overview of climate change and food security, Lobell and Burke (2010, p. 26) write that "[t]he utilization component of food security is perhaps its murkiest and least well-studied aspect." The lack of research on food utilization is also particularly evident in the assessment reports published by the Intergovernmental Panel on Climate Change (IPCC), which provides an overview of the state of knowledge on climate change. According to the most recent IPCC report for Asia, climate change projections show that the largest numbers of food-insecure people will be located in South Asia (IPCC, 2014). Nevertheless, the report focuses almost exclusively on food production and food supply, with virtually no mention of the nutritional elements of food security.

Although research on the effects of weather shocks on food utilization remain scarce, a related set of studies look at health indicators. This wide-ranging literature has considered outcomes such as infectious and non-infectious diseases, early life health, mortality, and psychological well-being (e.g., Andalón et al., 2016; Cornwell & Inder, 2015; Groppo & Kraehnert, 2016; Hyland & Russ, 2019; Kumar, Molitor & Vollmer, 2016; Lohmann & Lechtenfeld, 2015; Maccini & Yang, 2009; Pailler & Tsaneva, 2018; Watts et al., 2015). Yet, many of these studies do not explore nutrition directly, and only few papers have delved into the effects of droughts on the quantity and quality of household diets (e.g., Hou, 2010; Dillon, McGee, & Oseni, 2015; Baez, Lucchetti, Genoni, & Salazar, 2016).

Given the above research and policy knowledge gaps on food utilization, this paper extends the existing literature in two ways. First, I examine a question that has so far remained fairly understudied in the literature on rainfall and food security: in what ways do droughts impact how households utilize food as well as the energy and macronutrient composition of their diet? Second, in addition to studying effects on nutrition, I investigate the relative importance of prices and income as mechanisms. Thus, in comparison to much of the academic and policy discourse which focuses on food production and availability, I put the spotlight on socio-economic factors impeding food access. Furthermore, although the main thrust of this paper lies in food utilization, this study also speaks to the fourth pillar, stability, by providing insights on the poor's food consumption, especially during weather-related shocks.

To investigate the above questions, I turn to the context of households in rural India. Rural India represents a particularly interesting research setting because rain-fed agriculture accounts for more than 50 percent of the country's net sown area and 40 percent of total food production (Ministry of Agriculture, 2017). Thus, low levels of precipitation may have significant effects on food consumption. Additionally, almost 70 percent of the country's population live in rural areas (World Bank, 2015), where households derive their earnings primarily from the agricultural sector and where much of the country's food insecure population resides. Finally, as shown in Table 1, rainfall patterns in India vary substantially across both districts and years, with 30 to 80 percent of districts experiencing below-average rainfall in any given year. In the following section, I discuss the rainfall data, the measure of rainfall shocks and their spatial and temporal variability, and the household consumption data in greater detail.

[Table 1 here]

3. Data sources and summary statistics

3.1. Data sources

Rainfall data. I use precipitation data collected by Willmott and Matsuura (2015) at the

University of Delaware (henceforth, referred to as “UDel” data) to identify rainfall patterns in each district. These data contain monthly total precipitation for the years 1900 to 2014, gridded at a resolution of 0.5 degrees (approximately 30 miles, or 50 kilometers, at the equator). While gridded precipitation data with finer resolution are available from other sources (e.g., CHIRPS, Aphrodite), I use the UDel data because it has the temporal coverage that is necessary for my empirical design. The UDel data has also been used frequently for economic analyses of climate change, including by India's Ministry of Finance (e.g., Dell et al., 2014; Jayachandran, 2006; Shah & Steinberg, 2017; Kumar & Tulsidas, 2018).

I follow several previous studies (e.g., Blakeslee and Fishman, 2018) to match the gridded data to districts. In particular, I calculate the proportion of each district’s land area that is covered by a given grid pixel. These proportions are then used as weights to obtain the weighted average of monthly rainfall in a given district. Aggregating the monthly UDel precipitation data to the annual level, I define a dry shock in a given district to be the absolute deviation of rainfall, in meters per year, below the district’s long-run mean (i.e., over the four-decade period from 1973 to 2012). This definition of a district-level dry shock is similar to existing studies such as Sekhri and Storeygard (2014). While some district borders have changed over time, I use boundaries based on the 2001 Census of India throughout this study. Hence, I consolidate new districts that were formed between 2001 to 2012 back to their parent district.

National Sample Survey (NSS) Consumer Expenditure data. For my main outcome variables, I employ detailed household data from the NSS Consumer Expenditure surveys (Schedule 1). The NSS data I use in this study come from survey rounds 60 to 64, 66, and 68, corresponding to January 2004 to June 2008, July 2009 to June 2010, and July 2011 to June 2012. With the exception of Round 60 that was carried out from January to June, each survey round of the NSS was implemented from July to June. The NSS makes an effort to spread out its activities during the survey period so that in a given district, different villages are visited every quarter.[3] As a result, the vast majority of districts contain observations in all four quarters of the year.

The NSS surveys ask households to report total value of consumption in Rupees and total quantities consumed over the last 30 days for an extensive range of food items such as cereals, pulses, vegetables, fruits, and meat. In addition, the surveys request households to include consumption from all sources such as market purchases, in-kind transfers, and home production, thus providing a full image of household food consumption. Taking all possible sources of food into account is particularly important in the rural Indian setting since many individuals may be rural laborers who receive in-kind wages or are subsistence farmers. Following the NSS, throughout this paper, the term *expenditure* denotes not only market purchase but also the value of consumption (in Rupees) from all of the aforementioned sources.

Central to understanding the effects of rainfall shocks on food utilization is a measure of household nutritional intake. To this end, I employ a nutrition chart based on Gopalan, Sastri, and Balasubramanian (1991) and reported in various NSS publications (e.g., NSS, 2001, 2007, 2012, 2014b). This chart reports the energy, protein, and fat content per unit of weight of different food items in the NSS survey. For example, it indicates that one kilogram of potato typically has 967 calories, 17 grams of protein, and 1 gram of fat. I therefore obtain the nutritional composition of household food expenditure by multiplying the quantities recorded in the NSS survey with the conversion factors specified in the nutrition chart.

Although using the nutrition chart to convert household survey responses to caloric, protein, and fat intake is a relatively straightforward accounting exercise, food consumption reported in the NSS surveys may not perfectly reflect household members' food intake for three reasons. First, individuals may consume meals outside the home, for instance, through employers or schools. The nutritional content of these meals is difficult to measure and is not captured in the household surveys. Second, households may provide meals to non-household members such as neighbors or helpers. Expenditure for these meals are included in the survey responses, but they do not contribute to the household's nutritional intake. Third, actual nutritional consumption may depend on how households prepare and cook food as well as food wastage. For instance, some nutrients may be lost during the cooking process.

I address the first two issues by using an adjustment factor defined as $(N_h + N_a) \div (N_h + N_o)$, as in NSS (2014b) and Eli and Li (2017). Here, N_h is the total number of meals taken by household members at home during the last 30 days, while N_a and N_o are the analogous figures for meals away from home and meals given to others (i.e., non-household members), respectively. This adjustment factor implicitly assumes that meals given and received enter symmetrically and the nutritional value of both types of meals are directly proportional with a meal at home.[4] Importantly, household-level data on N_h, N_a, and N_o are available in the particular NSS surveys rounds that I use. In contrast, information on food preparation, cooking methods, and food wastage are not collected in these surveys, so I am unable to account for such aspects. I therefore treat them as measurement error, which may lead to less precise estimates.

NSS Employment and Unemployment data. Because the NSS Consumer Expenditure data do not contain information on household income, I take advantage of the NSS Employment and Unemployment surveys (Schedule 10) to obtain measures of rural household livelihoods. The employment survey rounds that I use in this study are the same as those of the NSS Consumer Expenditure survey, except for Round 63 (July 2006 to June 2007) when the employment surveys were not fielded. The employment questionnaire asks each household member to report their work and non-work activities in the last week prior to the household's interview. I follow the NSS and classify these activities into the following three categories:

(1) Employed: working in the household enterprise as an own-account worker, employer, or helper; regular wage or salaried employee; casual wage laborers; those not able to work due to sickness or other reasons, though there was work in the household enterprise or had regular wage employment.

(2) Unemployed: those not working but seeking, or available for, work.

(3) Not in labor force: those attending school; those attending to domestic duties and other work for household use; recipients of rent, pension, remittance, etc.; those not able to work due to disability; casual workers who are unable to work due to sickness.

Among those who worked as either casual or regular salaried workers, the survey also asks about earnings during the last week. Throughout the analysis of employment and earnings outcomes, I restrict the sample to only those individuals between the ages of 15 and 59. Doing so again follows the conventions adopted in various NSS publications (e.g., NSS, 2013), which provide key indicators on employment and unemployment based on the 15–59 age group.

Rural Price Collection (RPC) survey. The RPC survey, implemented by the NSS, collects rural retail prices every month—fielded in a fixed set of 603 markets spread over 26 states—for a fixed basket of goods. The data are therefore at the market-month-product level. The data cover the years 2001–07 and 2009–11 and contain a large number of products consumed by rural households, including food items such as cereals, pulses, vegetables, and fruits. These data also form the basis for the Consumer Price Index for Agricultural and Rural Laborers, which is compiled and published by India's Ministry of Labor.

Two important issues must be noted regarding the quality of the RPC's price data. The first is that many observations are missing because some products are not always present in the data, while others are indicated with zero prices. To address this issue and to increase the signal-to-noise ratio, I collapse the data to the market-year level by taking the median price across months for a given market and year.[5] The second concern is that no data are available for the months of January 2001 to September 2001, October 2007 to June 2009, and July 2011 to December 2011. I drop the years that do not cover the full 12 months and lack data for either the fourth or first quarter of the year, which span an important agricultural season.

Department of Consumer Affairs (DCA), price monitoring data. Given that the RPC price data contains many missing values, I use a second dataset on prices that comes from the Price Monitoring Cell of the DCA. This dataset contains an unbalanced panel of districts at the monthly level from 2009 to 2016, which I compile from the DCA website.[6] The data contain the average price (retail and wholesale) of essential commodities in a given month and is collected by the DCA from the main market in a given district.

In comparison to the RPC survey, there are three important points to note about the DCA data. First, prices in the DCA data have substantially fewer missing values. For example, although the district-month panel is unbalanced, these monthly data cover almost all district-quarters: only 1 percent or less of district-quarters are missing for rice, gram, urad, and potato retail prices. The crop with the highest proportion of missing values is wheat, for which 6 percent of district-quarters have missing retail prices. This relatively more comprehensive price data from the DCA therefore allow me to consider the effect on prices at the monthly level.

Second, the goal of the DCA is to monitor prices of basic food products and to prevent shortages of basic necessities. Therefore, the DCA focuses its data-gathering effort on essential commodities only, whereas the RPC survey collects information on a large number of food items. In particular, the DCA does not collect prices for horticultural products. Therefore, while the RPC data allow me to look at effects on fruits and vegetables, such as spinach and banana, I am not able to do so using the DCA data.

Third, although the DCA data contain fewer missing values than the RPC data, the former include fewer districts. The RPC survey includes data from around 600 markets in over 350 districts, whereas the DCA price data are collected from one major market in each of at most 100 districts. Because of this trade-off between fewer missing data and a larger sample of districts, I analyze the effects of the dry shock on prices using both the DCA and RPC data.

Crop production statistics. I obtain district-level measures of crop production from India's Ministry of Agriculture and Farmers Welfare, Directorate of Economics and Statistics. These data include information on total production and area planted across districts for several different types of crops such as grains, pulses, root vegetables, nuts, and sugarcane. Although the crop production statistics are publicly available online from 1997 onwards, I use data only from 2004 to 2012 to correspond with the years covered in the NSS Consumption and Expenditure surveys.

Land use statistics. Irrigation is a critical aspect to consider when examining droughts, as the presence of irrigation may mediate the effects of a dry shock on agricultural production as well as household food consumption. To account for this factor, I collect data on irrigation from the Ministry of Agriculture's Land Use Statistics.[7] I then calculate the proportion of net sown area that is irrigated on net during each district-year, which serves as one of the control variables in all regression specifications.

Because around 13 percent of all district-years in my study have missing information on irrigation, I implement linear interpolation or extrapolation and use the resulting values in all regressions. Nevertheless, I examine robustness of my findings to missing irrigation data by excluding district-years that lack irrigation data from the Land Use Statistics. As will be discussed in the robustness checks section, doing so yields similar results, although the standard errors increase because of the smaller sample size.

Census of India, 2001. I further augment the above datasets with the 2001 Census of India, which consists of district-level demographic variables (e.g., population density, literacy rate, and unemployment rate). These data provide additional control variables in the regression analysis, which I explain further in Section 4.

3.2. Summary statistics

Since this paper aims to investigate how droughts impact food utilization, the main variables of interest consist of rainfall (as the explanatory variable) and food consumption (as the response variable). Tables 1 and 2 provide summary statistics for these measures. In Table 1, I report the mean and standard deviation (SD) of total annual rainfall levels across Indian districts for the years 2004–12, the proportion of districts in each year experiencing a dry shock, and the mean and SD of the absolute deviation of annual rainfall below the long-term mean. The table shows substantial variation in rainfall across space and over time. For example, in any given year, the SD of total annual precipitation across districts lies between 0.72 and 0.98 meters, with a mean of around 1.2–1.4 meters. The share of districts experiencing a dry shock also varies widely, ranging from 0.32 to 0.89 across the years. The median dry shock level across all district-years is 0.15 meters, and the overall distribution of the dry shock variable is depicted in

Figure 1. As can be seen in the figure, the dry shock distribution has a long right tail; the 90th and 99th percentiles of the distribution are 0.379 and 0.715 meters, respectively.

[Figure 1 here]

For the dependent variables, Table 2 presents descriptive statistics of rural household food consumption using NSS Consumer Expenditure survey data from rounds 2004–05, 2006–07, 2007–08, 2009–10, and 2011–12. This table details the averages and, in brackets, the SD of monthly household per capita food expenditure (in nominal Rupees) and daily per capita intake of calories (in kcal), protein (in grams), and fat (in grams). All of these outcomes have been adjusted using the factors described in the previous section. Moreover, to understand the quality and composition of rural household diets, Table 2 shows consumption values disaggregated into the following six food groups[8]:

(1) Cereals: such as rice, wheat, maize, millet, jowar, and barley.

(2) Pulses, Nuts, and Oilseeds: including gram, urad, peas, arhar, walnut, and oilseeds such as soybean and groundnut that are consumed directly as food (rather than processed into cooking oils).

(3) Vegetables and Fruits: such as cauliflower, spinach, and bananas; also includes roots and tubers such as potatoes, carrots, and onions.

(4) Meat, Fish, and Dairy: covers prawns and other seafood, milk and milk products, and eggs.

(5) Sugar, Honey, Oils, and Fats: covers visible fat, that is, those that can be easily seen and identified such as cooking oils, margarine, butter, and ghee.

(6) Processed Food and Beverages: such as bottled drinks, biscuits, cakes, and sauces.

[Table 2 here]

Several interesting patterns stand out from Table 2. First, cereals represent the most significant component of diet and food spending of rural households, and in subsequent empirical analyses I show this is true for drought and non-drought regimes. As can be seen in Table 2, the highest share of the average household food budget across all years is always devoted to cereal and cereal products. This large expenditure share is reflected in energy and nutrient intake: the greatest source of calories for the typical rural household comes from cereals, which provide an average of 1,300 to 1,400 calories per person per day or more than 50 percent of total daily calorie consumption. Similarly, households obtain most of their protein from cereals, which constitute 50 to 60 percent of total daily protein consumption. Overall, these patterns echo earlier studies such as Subramanian and Deaton (1996), who document that cereals make up the largest expenditure and calorie shares in rural India.

Second, and also consistent with Subramanian and Deaton (1996), the cost per calorie and unit of macronutrient differ substantially across food groups. To illustrate, consider the statistics for 2004–05 in Table 2. The average household spent Rs. 81 per capita per month on meat, fish, and dairy and obtained only an average of 168 calories per capita per day, translating to an expensive price of almost Rs. 490 per thousand calories. The most expensive food group was processed foods with Rs. 883 per thousand calories. At the other extreme, cereals were the cheapest source of calories and protein at Rs. 77 per thousand and Rs. 3 per gram, respectively.

Third, the diet composition of rural households is quite poor, especially when compared to the country's national nutrition guidelines. Hence, if a dry shock leads to lower food consumption and nutrition outcomes, it exacerbates the already precarious situation of rural households. On the one hand, average per capita protein intake is somewhat decent: in all survey years shown in Table 2, the typical household consumes about 58 to 62 grams of protein per person per day; these values are roughly in line with national protein requirements for a normal adult of around 60 grams per day for men and 55 grams for women (NIN, 2009). On the other hand, the average calories per capita lies between only 2,150 and 2,250 kcals per day.[9] In comparison, 2,400 calories per person per day is often cited as the minimum requirement in India and forms the basis of the country's poverty line threshold (see Deaton & Drèze, 2009; NIN, 2011). Hence, these statistics suggest that the average rural household fails to meet basic subsistence levels of energy intake.

In addition to consuming few calories, rural households consume relatively minimal levels of fat. Fats are a necessary element of human diet; they serve as vehicles for and promote the absorption of fat-soluble vitamins such as vitamins A, D, E, and K. At nine calories per gram, they also deliver large amounts of energy, though the descriptive statistics in Table 2 suggest visible fats are relatively more expensive than cereals as a source of calories. While Indian guidelines suggest that for a balanced diet, 20 to 30 percent of total daily calories should come from fats (see NIN, 2011), the average household's fat intake contributes to at most 18 percent of total calories in all survey years. At the same time, the guidelines also suggest no more than 60 grams of visible fats per day given that excessive consumption of fats causes many diseases (NIN, 2009). The average rural household remains far from this threshold, as daily consumption of oils, butter, ghee, and other cooking fats amounts to only 18 to 23 grams.

4. Empirical method

I exploit random year-to-year deviations of precipitation from its long-run mean as a measure of exogenous local rainfall shocks. Throughout this paper, I focus on negative rainfall shocks in a given district—where rainfall is below the district's long-run mean—rather than positive shocks given that food insecurity is a much greater concern during times of drought.

Indeed, several empirical studies have argued that more rainfall in the Indian context tends to generally be favorable (e.g., Jayachandran, 2006; Duflo & Pande, 2007).[10] My basic empirical framework then investigates how district- and household-level outcomes respond to low levels of precipitation in a given year.

I take advantage of the spatial and temporal variation in rainfall across districts to estimate two sets of log-linear regressions. The first uses district-level panel data to estimate a fixed effects model given by

$$ln(y_{dt}) = \beta DryShock_{dt} + \xi WetShock_{dt} + \varphi Irrigation_{dt} + \gamma_d + \lambda_t + \delta_t \mathbf{X}_d + \varepsilon_{dt}. \quad (1)$$

For district d in time t, the left-hand side variable $ln(y_{dt})$ represents the natural logarithm of food security-related outcomes (e.g., annual agricultural yields for cereals, pulses, and other crops; the average retail price of rice and wheat in a given district-month). In some cases, I also estimate the analog of equation (1) using data at the market level (e.g., the average retail price of food products in a given market and year).[11]

The right-hand side of equation (1) includes the following variables: $DryShock_{dt}$, the absolute deviation of rainfall in a given district below its long-run mean in meters per year (note that it equals zero when rainfall is above the long-run mean); $Irrigation_{dt}$, the proportion of net sown area that is irrigated in a given district-year; γ_d, district (or market) fixed effects to capture time-invariant characteristics; λ_t, time fixed effects to control for changes over time that are common to all districts; and $\delta_t\mathbf{X}_d$, year-interacted district characteristics from the 2001 Census. In addition, equation (1) includes $WetShock_{dt}$ as a control variable. This variable equals the deviation of rainfall above its long-term average in meters per year and is zero when rainfall is below the long-run mean. Although $WetShock_{dt}$ is not a variable of interest in this study, I include it in the regression to allow for a flexible functional form. Specifically, it permits positive rainfall shocks to have a non-zero effects on outcomes, rather than constraining the impact to be zero.

The parameter of interest in the above equation is then β, the coefficient on the dry shock. Since I implement a log-linear regression, $100 \cdot \hat{\beta} \cdot 0.15$ measures the average percentage change in outcomes during a median dry shock, that is, when total annual rainfall in the district is 0.15 meters below its long-term mean.

In comparison to equation (1), which considers outcomes at the district level, the second regression framework I employ examines the impacts of drought at the household level. To this end, I use the household-level analog of equation (1) with the form

$$ln(y_{idt}) = \beta DryShock_{idt} + \xi WetShock_{idt} + \varphi Irrigation_{dt} + \gamma_{d} + \lambda_{t} + \pi_{c} + \delta_{t}\mathbf{X}_{d} + \alpha\mathbf{H}_{idt} + \varepsilon_{idt}. \quad (2)$$

Here, the dependent variable $ln(y_{idt})$ represents the natural logarithm of per capita food expenditure or nutritional intake for household *i* in district *d* at time *t*, interviewed in calendar month *c*. I estimate this equation by pooling together multiple rounds of the NSS consumption surveys, and the regression does not include household fixed effects, as the NSS data are not a panel of households. For employment outcomes, I also estimate the analog of equation (2) for data at the household member level, with controls for individual characteristics.

The basic features of equation (2) are similar to that in equation (1) but with two notable differences. First, while the *DryShock* variable in the latter is measured at the district level, in the former it is at the household level. All households in the NSS surveys are asked to report their food consumption and expenditure over the last 30 days, but because fieldwork is divided into four quarters of the year, the interviews happen at different dates across the full sample. Hence, to align the precipitation shocks with the timing of the survey, $DryShock_{idt}$ in equation (2) represents the absolute deviation from the district's long-term mean of total rainfall in the past 12 months prior to household *i*'s survey month. Moreover, as there may be seasonal effects in food consumption, equation (2) controls for the calendar month of the household's interview, π_c.

Second, in addition to controlling for year-interacted district characteristics $\delta_t\mathbf{X}_d$ as in equation (1), equation (2) also controls for household characteristics with the vector $\mathbf{H}_{idt}$. Since the outcome variables I consider in equation (2) pertain to food expenditures and nutritional intake, it will be critical to control for characteristics—for example, the household gender-age composition—that may influence the types and quantities of food items households consume. The vector $\mathbf{H}_{idt}$ enables me to account for such factors, as it consists of dummies for the household's religion, social group (i.e., Scheduled Tribe, Schedule Cast, or Other Backward Classes), and the fraction of household members in different male/female age cells.[12]

Using equation (2), I investigate the effects of a dry shock on household consumption in total across all types of food as well as broken down by food groups. Because the regressors are expressed in logarithmic form, it is important to note that a small number of households report zero consumption for some categories of food, at a frequency of less than 2 percent across all households and survey years; the dependent variable will thus be undefined for these households. To address this issue, I adopt the same method as in Blakeslee and Fishman (2018) and Pakes and Griliches (1980): I replace the dependent variable with zero for all zero values of consumption and include a dummy variable in the regression for this data transformation.

Lastly, standard errors in equations (1) and (2) are clustered at the district level. This approach follows previous studies on the economic effects of weather in India, such as Burgess, Deschenes, Donaldson, and Greenstone (2017) and Sekhri and Storeygard (2014), who have argued the measurement errors are likely to be correlated within districts over time. Further, I explore robustness of the results to the potential spatial correlation of rainfall shocks by implementing spatially correlated errors as modeled in Conley (1999). The results from these alternative standard errors show similar patterns, as will be discussed in the robustness checks.

5. Empirical results

5.1. Effects on agricultural yields

As a point of departure, I demonstrate that low precipitation indeed leads to a statistically significant reduction in agricultural yields. Doing so serves to confirm the validity of my measure for a dry shock—the main regressor of interest throughout the study—and likewise to inform the succeeding analysis of effects on household diet and nutrition. Since the relationship between rainfall and agricultural production has already been widely studied (see earlier discussion in Section 2), this section may also be regarded as a replication exercise for the findings in the existing literature.

Table 3 shows results from estimating equation (1) for the outcome variable log agricultural yield, that is, production (measured in tons) divided by area planted (measured in hectares). In this table, I include the following five crops: two grains (rice and wheat), two types of pulses (gram and urad), and potato. I have chosen these particular crops because they possess several characteristics necessary for this empirical study. In particular, they have the most comprehensive coverage in the crop production data over time and across space, and they represent relatively substantial components of diet and food consumption among rural Indian households.

[Table 3 here]

Consistent with earlier papers on weather and agriculture in India, Table 3 highlights a stark negative effect of droughts on crop yields. The estimates suggest that for a median dry shock where annual rainfall is 0.15 meters below the long-term average, rice and wheat yields fall by 4 percent (column 1) and 3 percent (column 2) respectively, significant at the 1 percent level. Likewise, yields for pulses see a decline of 3.5 percent (column 3) for gram and 1.4 percent (column 4) for urad, while potato yields decrease by 1.5 percent (column 5). Further, these findings are in line with the fact that much rural Indian agriculture continues to be rain-fed.

5.2. Effects on food utilization

Having established the negative consequences of inadequate rainfall on agricultural output, I now consider the principal question of interest in this paper: how do droughts affect household food utilization, particularly the quantity and quality of their diet? I analyze this question by taking advantage of NSS Consumer Expenditure surveys. This dataset provides a complete picture of household food consumption, as it includes the quantity (e.g., in kilograms) and value (in Rupees) of consumption from market purchases, home production, and in-kind transfers. With these data, I estimate regression equation (2) where the outcome variables are per capita food expenditure, caloric intake, protein consumption, and fat intake. All of these outcomes are measured in logarithm at the household level, and I examine them both in aggregate across all food groups as well as disaggregated by each food category. In what follows, I adopt the convention used by the NSS (e.g., NSS, 2011) and use the term *expenditure* to encompass market-based spending, the value of outputs produced by the household and retained for own consumption, and the value of in-kind transfers received by the household (e.g., as remuneration, gifts from neighbors, etc.).

5.2.1. Aggregate food expenditure and nutrition

Table 4 reports results for household total expenditure (column 1), food expenditure (column 2), and macronutrient consumption (columns 3–5). In light of the large number of studies that have documented the detrimental effects of droughts on agricultural production, this table validates the view that the drop in crop yields is likewise accompanied by lower household food spending and nutrition. Indeed, all dry shock coefficients in Table 4 are negative and statistically significant at the 1 percent level. Given that the typical rural Indian household consumes only minimum or very low levels of calories, protein, and fat on a day-to-day basis, the results in Table 4 indicate that droughts put households even more below the recommended daily values for energy and macronutrient consumption.

[Table 4 here]

Nevertheless, in addition to empirically demonstrating the direction of the effects, it is important to understand the magnitudes of the impacts. Considering a median dry shock of 0.15 meters, I find that the negative effects on household consumption and nutrition are small. Specifically, total expenditure and food expenditure decrease by around 1 percent, and similarly, calorie, protein, and fat intake decline by at most 1.4 percent. Notwithstanding these magnitudes, the results provide empirical evidence that droughts do have detrimental consequences on household nutrition. Importantly, as will be discussed later in Section 6, my estimates may potentially provide a lower bound for the true magnitude of a drought's negative effects, as measurement error in the dry shock may result in estimates that are biased toward zero.

While household food consumption and nutrition are the primary focus of this study, I also present results for non-food spending in Table 5. Investigating the effects of the dry shock on non-food expenditure is particularly interesting for two reasons. First, because expenditure is often used as a proxy for income, effects on non-food spending may shed further light on the economic well-being of households during droughts. Second, non-food spending may have implications for food availability in the household. For example, periods of low rainfall may induce households to cut back on their non-food purchases to smooth out food expenditure. Alternatively, non-food spending may squeeze the household's food budget.

[Table 5 here]

As can be seen in Table 5, droughts negatively impact all types of non-food expenditures that I study. This includes total non-food spending (column 1); clothing, bedding, and footwear (column 2); durable goods (column 3); educational and medical goods and services (column 4); and fuel and lighting (column 5). The largest negative effects are seen for education and medical purchases, where a median dry shock results in 3 percent lower spending. Although all dry shock coefficients in Table 5 are negative, they are estimated with less precision relative to those for food consumption outcomes in Table 4, as expenditure data on infrequently purchased items (e.g., durable goods) tend to be noisier than those on frequently purchased products (e.g., food). Still, the results in Table 5 do not lend support to the idea that non-food spending squeezes the food budget during a dry shock.

To further investigate the possibility that non-food consumption puts pressure on food consumption during droughts, I implement a Seemingly Unrelated Regression Equations (SURE) model with a system of two equations: one where the outcome is log food expenditure (Table 4, column 2) and the other for the outcome log non-food expenditure (Table 5, column 1). I then conducted a test of equality of the dry shock coefficients across the two equations. This test yields a p-value of 0.1144. Hence, at the 10% level, I am unable to reject the null hypothesis that both coefficients are equal.

I also examine the confidence intervals of the dry shock coefficient across the two regressions with log food expenditure and log non-food expenditure as outcome variables. If the 90% confidence intervals of these coefficients do not overlap, this would imply a statistically significant difference at the 10% level. Using the Ordinary Least Squares estimates on the dry shock for the outcome log food expenditure (Table 4, column 2) and log non-food expenditure (Table 5, column 1), I find 90% confidence intervals of (-0.100, -0.036) and (-0.084, -0.0002), respectively. In other words, more than half the length of the latter confidence interval is contained in the former. Consistent with the results from the joint test in the SURE model, this substantial overlap in the confidence intervals indicates that at the 10% level, the difference between the two coefficients is unlikely to be statistically significant.

5.2.2. Disaggregated food expenditure and nutrition, by food group

To better understand household food utilization in the face of droughts, this study examines household food consumption not only as a whole but also across different types of food. In this section, I delve into the dynamics underlying the reduction in household's total food and nutrient consumption by disaggregating the effects into the following six food groups: (1) cereals; (2) pulses, nuts, and oilseeds; (3) vegetables and fruits; (4) meat, fish, and dairy; (5) sugar, honey, oils, and fats; and (6) processed food and beverages. Table 6 then presents these disaggregated results, where each column represents one particular food category and each panel corresponds to one particular outcome variable.

Generally speaking, the estimates show that low rainfall leads to lower food expenditure and nutrition for every type of food item: the dry shock coefficients are negative for all six food groups and all consumption outcomes. However, the magnitude of the impacts varies across food categories, providing indications of where major nutritional gaps may be during droughts. For instance, while outlays for and macronutrients from cereals, animal products, and processed foods all decline, the effects in percentage terms are much smaller for the former relative to the latter two groups. More specifically, the estimates in Table 6 illustrate the following four patterns describing how rural households allocate their food spending, which foods they obtain macronutrients from, and what deficiencies exist in their diet when confronted with a dry shock.

[Table 6 here]

Pattern 1. Households continue to rely heavily on cereals. This pattern is evident in that the smallest effect of poor rainfall on food expenditure can be seen in cereals, where a median dry shock of 0.15 meters results in a 0.7 percent decrease in spending (column 1, Panel A). Similarly, the smallest percentage declines in calories, protein, and fat intake can be observed in cereals at around 0.2 to 0.5 percent for a median dry shock (column 1, Panels B–C). For the average rural household, cereals constitute the largest share of the food budget and the primary source of calories and protein. These patterns thus indicate that cereals remain as the biggest component of food utilization even during droughts. In addition, it is consistent with the idea that cereals are a cheap source of energy and protein relative to all other food groups.

Pattern 2. Households shift away considerably from processed food products and animal-based foods. Whereas cereals exhibit the smallest effects, the largest impacts of the dry shock in percentage terms come from processed food and beverages (e.g., bottled drinks, biscuits, sauces). For processed foods, a median dry shock of 0.15 meters brings 1.3 percent less expenditure and up to 5 percent less intake of calories, protein, and fat (column 6, Panels A–D). Likewise, for meat, fish, and dairy products, a median dry shock results in a statistically significant decline of 1 percent in spending (column 4, Panel A). This lower spending on animal products corresponds to lower calories, protein, and fat consumption as well, with a magnitude of around 1 percent for a median dry shock (column 4, Panels B–C).

Households largely substituting away from processed and animal-based products during droughts may be due to the high income elasticity of these food items. Processed foods and meat are typically consumed by richer and/or more urban households, and prior economics research has shown that these products are luxury goods in the rural setting, as they have an income elasticity greater than one (e.g., Kumar, Kumar, Parappurathu, & Raju, 2011). Importantly, as will be shown later in Section 5.4, the dry shock lowers household income by decreasing employment and daily earnings and increasing unemployment. Thus, when experiencing low rainfall, rural households significantly reduce their expenditure for highly income elastic goods such as processed and animal-based foods.

Pattern 3. Households forgo food products that bring palatability and taste. The results show that a median dry shock corresponds to 1.2 percent less monthly spending per capita on sugar, honey, oils, and fats, statistically significant at the 1 percent level (column 5, Panel A). This finding suggests that low rainfall deters rural households from purchasing items that contribute to the texture, aroma, and taste of food, likely in an effort to economize on spending. Nonetheless, apart from adding flavor, visible fats (such as cooking oils, butter, ghee) represent an important source of fat nutrients in everyday diets. The reduced expenditure in these items during a median dry shock therefore translates to a 1.2 percent decrease in consumption of fat per capita, again significant at the 1 percent level (column 5, Panel D). Further, fat provides twice as much energy than carbohydrates, so the lower availability of visible fats also brings fewer calories per capita, with a magnitude of 0.7 percent for a median dry shock (column 5, Panel B).

Pattern 4. Households consume less naturally nutrient-rich foods. Finally, Table 6 reveals that in times of drought, rural households spend less money on food products that are naturally rich in nutrients: a median dry shock corresponds to 0.7 percent less expenditure on vegetables and fruits (column 3, Panel A) and almost 2 percent less spending on pulses, nuts, and oilseeds (column 2, Panel A); the calories and protein households obtain from these two food categories also decline substantially. Indian national dietary guidelines recommend eating plenty of vegetables and fruits, as they are good sources of vitamins and minerals as well as non-nutrients such as fiber and antioxidants; the guidelines likewise prominently feature pulses, nuts, and oilseeds due to their high protein content (National Institute of Nutrition, 2011). Hence, my findings indicate that droughts impede rural households from adhering to nutrition guidelines and including more nutritious foods in their everyday diet.

5.3. Effects on prices

The results from the previous sections have shown that droughts negatively and statistically significantly impact household food utilization. But through what channels do these effects operate? One potential mechanism is food prices, which I investigate in detail in Table 7. This table uses data from the RPC survey to estimate regression equation (1), where the outcome variables are log rural retail prices of wheat, rice, gram, urad, potato, spinach, and banana. With the addition of spinach and banana, the table includes the same products as in Table 3, which demonstrate a decline in agricultural yields due to droughts. As before, I have selected the food items in Table 7 because of their extensive coverage in the data and relative importance in rural household diet and food expenditure. Retail prices are defined as the median retail price across all months reported in the data in a given market-district-year.

[Table 7 here]

As can be seen in the table, the dry shock coefficients are generally positive, but they are, by and large, statistically insignificant. In other words, I am unable to reject the hypothesis that droughts have no impact on food prices. Importantly, this null effect is consistent with several previous studies: for instance, using daily wholesale prices, Zimmermann (2017) argues that storage and re-optimization across space makes Indian rice prices less sensitive to weather. Additionally, Blakeslee and Fishman (2018) describe little food price variability across Indian districts, as agricultural markets have become increasingly integrated over time due to transport infrastructure. Together with these results from the existing literature, my findings offer suggestive evidence that prices may be quite unresponsive to rainfall in the Indian context.

Nevertheless, as described in Section 3, the RPC data used in Table 7 have many missing values, so it is important to examine whether the above patterns hold for other sources of price data. To this end, Table 8 shows regressions using prices from the DCA, which is an unbalanced panel of average daily retail and wholesale prices at the district-month level from 2009 to 2016. The data are collected by the DCA’s Price Monitoring Cell from the main market in a given district. Even with this alternative and more complete price data, the results in Table 8 confirm the null effect of a negative dry shock. For retail (Panel A) and wholesale (Panel B) prices, none of the estimates are statistically significant. Furthermore, none of the coefficients are economically significant, as the magnitudes are by and large close to zero.

Panels C and D of Table 8 provide an additional robustness check for the null price effects. Here, I replicate the regressions in Panels A and B but restrict the sample to only those months in the post-monsoon season, when largest impacts of the dry shock may occur as the main cropping cycle has ended. The post-monsoon season is defined as the months October to December, following the Indian Meteorological Department (Attri & Tyagi, 2010). Similar to Panels A and B, the coefficients in Panels C and D are all statistically insignificant, and many are close to zero in absolute terms. Thus, the dry shock appears to have no impact on food prices during the post-monsoon season as well. These findings are reassuring, as they lend further support to the conclusion that food prices do not respond much to droughts.

5.4. Effects on employment and earnings

The pathways of the effects of low rainfall on household food utilization may include not only the price of food but also income. Hence, to understand the consequences of droughts for the livelihood of rural households, Table 9 presents regressions of employment and earnings on the dry shock using the specification in equation (2). Because the NSS Consumer Expenditure surveys do not collect information on household income, my analysis in Table 9 uses the NSS Employment and Unemployment surveys. These surveys ask all household members to report their time allocation in the last seven days and, among those who worked as casual or salaried workers, their earnings over the same period. Accordingly, the outcomes in Table 9 are the proportion of days in the last week that the respondent spent employed (column 1), unemployed (column 2), or not in the labor force (column 3) and log earnings per day worked (columns 4–6).

[Table 9 here]

The results in Table 9 reveal three interesting insights. First, the dry shock does not influence labor force participation. Indeed, the coefficient estimate for this outcome is very close to zero and is not statistically significant. Second, droughts lead to a decline in the proportion of days worked in the last week, and likewise, an increase in the proportion of days without (but available for) work. These effects are statistically significant at the 5 and 1 percent levels, respectively. Furthermore, the magnitudes of impact mirror each other: for employment, the dry shock coefficient is -0.015, whereas for unemployment, it is 0.012. Finally, the lower employment levels due to droughts translate into lower average daily earnings across all sectors. In particular, droughts result in lower earnings whether we consider earnings from all activities, agricultural activities only, or non-agricultural activities only.

5.5. Heterogeneity of effects

Thus far, I have focused on the average effects of the dry shock on household food consumption, nutrition, and food utilization. In this section, I examine the differential impacts of droughts along three dimensions: (1) whether female-headed households handle droughts differently than male-headed households; (2) whether the dry shock's impact depends on the season; and (3) whether the effect of the dry shock varies on the district's prior rainfall realizations.

[Table 10 here]

5.5.1. By gender of the household head

Investigating how droughts impact food security among female-headed households is an important policy question, as women are often confronted with many more social and economic constraints than men. For instance, women face restrictions in their mobility outside the home and tend to be relatively disadvantaged in the labor market. Female household heads, as the main income-earning member of the family, take responsibility for non-household production but must also attend to household production such as child care and domestic chores (Mallick & Rafi, 2010; Flatø, Muttarak, & Pelser, 2017). Thus, the consequences of drought may be much more severe for households that are headed by women. In the data, these female-headed households comprise around 10 percent of all households in any given survey round.

Table 10, Panel A tests for differences in the effect of the dry shock by the gender of the household head. The regressions in this table interact the dry shock with a dummy for female-headed households. Correspondingly, the coefficient of interest is that of the variable *Dry shock * Female head.* The results suggest that droughts have similar effects on food consumption and nutrition across male- and female-headed households. In particular, the coefficient on the interaction term is very close to zero and is not statistically significant for almost all outcome variables. The sole exception is the outcome related to fat consumption, where the interaction term is negative and is statistically significant at the 5 percent level. This finding indicates that when a dry shock occurs, female-headed households reduce consumption of fatty products (e.g., cooking oils, ghee, meat) to a much larger extent than male-headed households.

5.5.2. By season

While Table 10, Panel A examines differences in the effects of the drought by the gender of the household head, Panel B investigates whether rainfall shocks have a seasonal effect. Because the NSS Consumer Expenditure surveys ask households about their consumption during the last 30 days, differences in when households are interviewed may matter for the magnitude of the dry shock impacts. For example, although the average effect of the dry shock that I find is small, this modest average effect may mask larger negative effects during the agricultural season, the time of year when droughts may have greater implications for rural household livelihoods.

To this end, Table 10, Panel B interacts the dry shock with an indicator variable for whether the household was interviewed during the cropping season. Here, the cropping season is defined as the calendar months June to February; these months coincide with the southwest monsoon, northeast monsoon, and winter seasons and they likewise roughly span the *kharif* (autumn) and *rabi* (winter) agricultural seasons. As seen in Panel B, the coefficients on the interaction term are all negative. However, most are small in magnitude and not statistically significant, apart from the interaction coefficient corresponding to the outcome variable for calorie consumption.

5.5.3. By past dry shock

In addition to season, a second aspect that may have implications for size of the effects is a district's past experience with dry shocks. In other words, in a given district, does the impact of the drought in this period depend on whether a drought also occurred in the previous period? To explore this issue, I interact the dry shock with an indicator for whether the one-year lagged dry shock is positive. This indicator is equal to one if total rainfall in the penultimate 12 months before the household's interview month is below the district's long-term mean. The results in Table 10, Panel C show that the interaction terms are all positive, and some are statistically significant at the 5% level. These findings therefore suggest that after encountering a drought, households are better able to cope with a dry shock.

These results also provide suggestive evidence that households may be learning how to manage droughts in the short-run—an interpretation that is consistent with previous studies on India, which have demonstrated the ability of Indian farmers to adapt to droughts and climate change. For instance, Taraz (2017) shows that Indian farmers alter their irrigation investments and crop portfolios in response to medium-run variability in rainfall, though doing so has only limited impact on improving farmers' profits. In line with adaptation, Taraz (2018) also finds that yield losses from high temperatures are lower in heat-prone districts.

Moreover, the magnitudes indicate that the negative effect of the dry shock in the current period is about 50% smaller in districts that experienced a dry shock in the prior period, relative to those that did not. This large difference potentially indicates that when households are again confronted with a drought, they implement multiple strategies to ensure food stability. These shock-coping mechanisms may include temporary migration, formal and informal insurance, borrowing, buffer stocks, and government social programs, and they have been widely studied in the existing literature (e.g., Skoufias, 2003; Castells-Quintana et al., 2018). However, due to data constraints, I am unable to determine specifically which strategies households may be using, as the NSS data lack information on migration and households' finances.

5.6. Robustness checks

Finally, I examine whether my empirical results are robust to different control variables, data sources, regression specifications, and regression error structures. I explain these robustness checks in more detail in Appendix A. For brevity, I present results only for the main findings on aggregate food consumption and nutrition, but the patterns are qualitatively similar for the results disaggregated by food group. As can be seen in Appendix Tables A1 to A7, my results and conclusions remain unchanged when (1) adding temperature as a control variable in the regression; (2) using alternative rainfall data; (3) employing alternative definitions of a dry shock; (4) examining effects with the intensity of rainfall shocks; (5) using spatially correlated errors; (6) measuring household food consumption and nutrition outcomes in levels rather than logs; (7) allowing intercepts to differ between positive and negative rainfall shocks; and (8) excluding district-years with missing irrigation data. Thus, the substantial negative effects of a dry shock on household food utilization I observe are unlikely to be due to biases from omitted control variables or misspecification of the functional form.

6. Discussion and conclusion

Over the past two decades, the Indian government has introduced a number of key schemes to ensure food security for the poor, including mid-day meals for school children, rations for pregnant and lactating mothers, and subsidized food through the public distribution system (UN, 2017). In addition, the National Food Security Act (NFSA), signed into law in 2013, entitles three-fourths of the rural population to five kilograms of rice, wheat, and coarse cereals per month at a highly subsidized price of one to three Rupees (i.e., US$ 0.01–0.04) per kilogram (Kishore, Joshi, & Hoddinott, 2014). Although these programs are not without flaws such as leakages and high implementation costs (see Khera, 2011; Drèze & Khera, 2015), my findings suggest that such food security initiatives are ever more relevant and necessary in periods of low rainfall, as droughts statistically significantly and negatively impact household food spending and macronutrient intake (Table 4).

At the same time, my disaggregated analysis by food group shows that dry shocks result in dietary deficiencies (Table 5). Across the globe, as well as in India, nutritionists' first dietary recommendation is to "eat a variety of foods" since a diverse diet is more likely to bring the full range of vitamins and nutrients necessary for a healthy and active life (NIN, 2011; FAO, 2013). Yet, my results show that droughts lead households away from a balanced diet: they substantially decrease their consumption of fruits, vegetables, legumes, and animal-sourced foods during a dry shock and instead rely primarily on cereal products. These results imply that achieving food security in times of extreme weather requires an integrated approach that focuses not only on consumption quantity but also on diet quality. For instance, although subsidized cereals supplied through the NFSA may increase the amount of food that households eat during a dry shock, the NFSA may not fully address diet diversity, as it focuses only on cereals. Thus, programs combining subsidized grains with other approaches may be essential for attaining food and nutrition security in the face of droughts.

Understanding the channels through which rainfall shocks result in lower household food expenditure and nutrition provide insights for crafting comprehensive food security programs that address diet quantity and quality. My results on prices, employment, earnings, and agricultural production speak directly to this issue: I find that droughts do not affect the first of these outcomes but induce a drop in the latter three. Therefore, the negative impacts of droughts on household food utilization likely operate primarily through effects on income (broadly defined as livelihood generating activities) rather than through food prices. This mechanism influences the ability of farm and non-farm households to access food during droughts.

Specifically, for households who engage in subsistence agriculture, their food consumption and nutrition outcomes are made worse off by droughts because agricultural yields, which can be thought of as non-market income, decrease (Table 3). Similarly, for households self-employed in agriculture who are net producers of food, their livelihood dwindles: a lower quantity of output is available for consumption at home and/or to sell in the market, and the decrease in output is not offset by an increase in crop prices (Table 6). Furthermore, for households employed as casual or salaried workers, whether in the agricultural or non-agricultural sector, labor income falls as a result of droughts (Table 9). Overall, these results underscore the critical role that market and non-market incomes play in revealing why aggregate food consumption and nutrition decline with a drought. They likewise parallel a broader literature on the impact of rainfall shocks on crime and conflict, which has stressed income as the principal mediating factor (e.g., Miguel, Satyanath, & Sergenti, 2004; Blakeslee & Fishman, 2018).

While I find statistically significant impacts of drought on nutrition, the magnitudes of the effects merit further discussion. Indeed, my results show that a median dry shock of 0.15 meters leads to lower household food spending, calorie consumption, protein intake, and fat intake of at most 1.4 percent. One potential explanation for these modest coefficients is classical measurement error in the dry shock variable. This variable may be measured with error because the underlying gridded rainfall data are interpolated over space and time using available weather station data. If measurement error exists and is uncorrelated with the true rainfall level, this would lead to attenuation bias. In this case, the coefficient estimates I find are biased towards zero and provide a lower bound in absolute terms for the true negative effects of the dry shock.

In the context of South Asia, previous studies comparing gridded precipitation products with observed rainfall from weather stations have shown that gridded data from UDel, which is the rainfall dataset I employ in this study, outperform that from the CRU (e.g., Ahmed et al., 2019). This pattern is consistent with measurement error and attenuation bias, as I find that the negative effects of the dry shock are much smaller when using CRU (Appendix Table A2) compared to using UDel (Table 4). Moreover, classical measurement error is amplified due to regression fixed effects (e.g., Angrist & Krueger, 1999). This amplification may explain why the coefficient estimates I find are modest not only for food consumption and nutrition outcomes, but also non-food expenditure, employment and earnings.

A second possible explanation for the modest effect sizes is that the coefficients are biased because of omitted variables. I acknowledge that I am unable to rule this out completely. However, the patterns in the empirical results appear to support the interpretation of measurement error rather than omitted variables. As can be seen in the robustness checks, the magnitudes of the coefficients change substantially only when using alternative rainfall data. The estimates remain the same when control variables are added, when applying different functional forms to the dependent and independent variables, or when the subsample with missing irrigation data is excluded from the estimation. These findings suggest that the potential biases are due to measurement error in the dry shock rather than omitted variables or regression misspecification. Furthermore, I find effects on agricultural yields that are very similar to previous papers that have also used gridded precipitation data from UDel but with a different definition of a drought (e.g., Mahajan, 2017), providing a reassuring sanity check for my results.[13]

Apart from measurement error or omitted variables, it is also possible that the small effect sizes arise because households are able to smooth out the negative consumption effects of a median dry shock. I recognize that I am unable to examine this issue in detail because the NSS Consumer Expenditure data do not contain detailed information about households' savings, loans, and other finances. Still, my findings suggest that two particular consumption-smoothing strategies may not be fully at play. Specifically, I do not find evidence that households are shifting their expenditures to smooth out food consumption, as the effects of the dry shock on food and non-food expenditure are not statistically different from each other (Tables 4 and 5). Moreover, I find statistically significant and negative effects of droughts on both employment and earnings (Table 7), indicating that households may not be able to fully cope with the dry shock by diversifying their income streams.

Finally, my study has important limitations. While my empirical strategy—which takes advantage of random year-to-year deviations of rainfall from its long-term average—allows for estimating causal effects, doing so captures only short-term impacts. In particular, I am unable to incorporate adaptation, the effects of persistent rainfall, and other factors that are important for the long-run effects of a changing climate. To assess such long-term impacts, a different data structure and a different empirical method (e.g., long differences) would be necessary. In addition, since my empirical design focuses on dry shocks at the district level, I am unable to investigate aggregate effects. For instance, droughts and climate change that impact general equilibrium at the national or global level are not accounted for in my analysis. Estimating such effects would require quantitative structural methods which are beyond the scope of this study.

Despite these necessary shortcomings, this paper contributes to our understanding of the consequences of droughts for household food utilization, an issue that remains understudied in the existing literature. In addition, my study sheds light into the mechanisms through which droughts result in lower food consumption and nutrition among rural households. I find that droughts have a statistically significant and negative effect not only on the amount of food that rural households eat but also the diversity and nutritive value of their everyday diet. Moreover, I show that relative to food prices, market and non-market incomes play more important roles as mechanisms for the effects. Nevertheless, many important issues remain unanswered in this study, including gender, coping and adaptation mechanisms, persistent droughts, and long-term impacts. Investigating whether droughts lead to more severe consequences for the nutrition of women and girls, what strategies households employ to adapt and cope with persistent negative rainfall shocks, and how dry shocks impact household nutrition over the long-term remain important avenues for future research.

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Appendix A. Robustness checks

Adding temperature controls. Regression equations (1) and (2) contain district fixed effects γ_d that absorb spatial characteristics as well as time fixed effects λ_t that take into account common temporal trends. To the extent that weather variation is exogenous, the coefficient β in these regressions thus allow for capturing the causal effects of a dry shock on household food consumption. Nonetheless, there may be omitted variable bias in estimating β, particularly due to the potential correlation between temperature and rainfall. To address this issue, Appendix Table A1 shows regression results when including temperature—defined as the average monthly temperature over the last 12 months prior to the household's survey date—as a control variable in the regression. As can be seen in the table, the estimates are remarkably similar to Table 4 with very little change in the coefficients.

Alternative rainfall data. My empirical analysis employs gridded rainfall data from Willmott and Matsuura (2015), which includes detailed land surface temperature and precipitation climatology for all of India. Each of the gridded monthly values for temperature and precipitation values is a local estimate at 0.5x0.5 degrees, which may more accurately represent spatial variability than grid-cell average data (Matsuura et al., 2017). However, because the data has been interpolated among ground stations, measurement error remains a concern. For instance, the accuracy of interpolation depends on the coverage of the ground station records, and different interpolation methods may result in different estimates as well.

Given that rainfall is a main independent variable of interest throughout this study, I check for the robustness of my results by instead using rainfall data from the Climatic Research Unit (CRU) at the University of East Anglia. Similar to Willmott and Matsuura (2015), the CRU data are also gridded at 0.5x0.5 degrees, but the underlying ground station records and extrapolation algorithms somewhat differ (Auffhammer, Hsiang, Schlenker, & Sobel, 2013). The regression estimates with CRU data are reported in Appendix Table A2. Again, I find significant negative effects of drought on food consumption and nutrition, although the magnitudes of the coefficients are somewhat smaller than those of the main results in Table 4.

Alternative definition of dry shock. Thus far, I have investigated the effects of a negative rainfall shock measured in levels. In other words, the *Dry Shock* variable is defined as the absolute deviation in meters per year of total yearly rainfall below the district's long-term annual mean. But the impact of a one-meter dry shock may not be comparable across agroclimatic zones, as some areas may have drier or wetter climates than others. I therefore allow for rainfall shocks that are more comparable in magnitude across regions by considering an alternative definition of dry shock that is measured in units of SD.

Appendix Table A3, Panel A shows results for the effects of this alternative definition of negative rainfall shocks on household consumption and nutrition outcomes. In this table, the regressor is *Standardized Dry Shock*, obtained by dividing the previously defined *Dry Shock* variable with the district's long-term SD of annual rainfall. Notably, the patterns in this table are qualitatively similar to that in Table 4, where the independent variable is *Dry Shock*. For example, the results show that when rainfall is one SD below the long-term mean, households food expenditure falls by 1.8 percent.

In addition to the *Standardized Dry Shock*, Appendix Table A3, Panel B also reports results for a regression where the independent variable is *1(Rainfall < 20^{th} Percentile)*, a dummy variable for rainfall that is below the 20th percentile within the district over a long-term period (i.e., 1973 to 2012). This definition of a dry shock follows Shah and Steinberg (2017), who examine the impact of droughts on human capital. As before, the results are quite similar. The main difference appears to be in the results for protein, which does not attain statistical significance when using the drought indicator variable.

Intensity of rainfall shocks. I next consider the possibility that effects vary with the intensity of the rainfall shock. Specifically, I regress household consumption and nutrition outcomes on dummy variables representing bins of the standardized rainfall measure, including positive and negative deviations from the long-term precipitation average. This analysis enables me to investigate two key ideas: first, whether there may be non-linearities in the impacts of rainfall and second, whether positive shocks are indeed beneficial for households in the rural Indian context, as explained earlier in Section 4.

The regression results are reported in Appendix Table A4. Here, each bin is 0.75 standard deviations wide, and the bin centered at zero is the omitted category in the regression. The effects are generally consistent with those in Table 4. The magnitude of the negative effects become larger as the dry shock becomes more severe, and much of the negative impacts of poor rainfall are concentrated with the driest shocks. Importantly, the results also show that the effects of the wet shock are positive. These findings therefore support the argument that household food security and food utilization is a greater concern during times of drought.

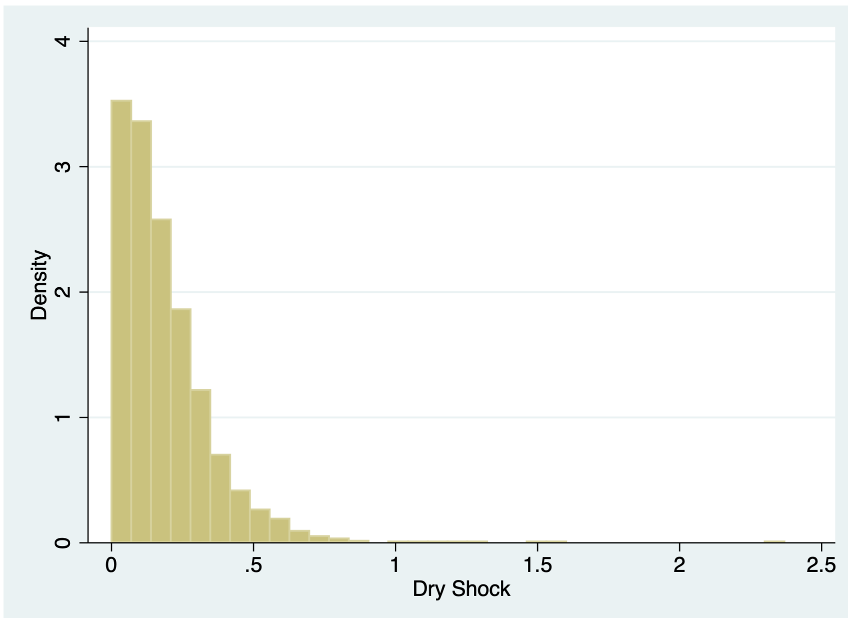
Spatial correlation of rainfall shocks. Throughout this paper, I have clustered standard errors at the district level following Burgess et al. (2017) who have argued that measurement errors are likely correlated within districts over time. Appendix Table A5 checks the robustness of my main results to the spatial correlation of rainfall shocks following Conley (1999). In each panel of this table, I use a temporal lag of zero, one, or two years and a spatial lag of 100 or 200 kilometers.[14] While the standard errors do increase, my findings are unchanged, as all coefficients are still statistically significant at the 1 percent level.

Outcome variables in levels. In this study, I express the outcomes in logarithms primarily because the outcomes are highly skewed. For example, Appendix Figure 1 shows the distribution of monthly household per capita total expenditure, food expenditure, calorie intake, protein intake, and fat intake. As can be seen in this figure, the distribution is positively skewed and approximately log normal. Taking the natural log therefore transforms the variables so that they become normally distributed. Nevertheless, in Appendix Table A6, I consider the robustness of my results to the functional form of the dependent variable. Specifically, I examine the effects of the dry shock on outcomes in levels—that is, in Rupees for expenditures, in kcals for calories, and in milligrams for protein and fat. The results show that the effect of the dry shock is still negative. While the coefficients corresponding to the expenditure outcomes are not statistically significant, those for macronutrient intake are all statistically significant at the 1 percent level.

Flexible intercept. As an additional robustness check regarding the functional form, I also estimated regressions where I include an indicator variable for rainfall below the long-term average as a regressor. This indicator variable permits a flexible regression specification, as it allows the intercept to differ between positive and negative rainfall shocks. The regression estimates are shown in Appendix Table A7. As can be seen in the table, the coefficients remain very similar to the main effects in Table 4. Therefore, the results are robust to allowing for differences in the intercept of dry and wet rainfall shocks.

Missing irrigation data. Finally, as mentioned in the data sources section, the control variable for irrigation was interpolated or extrapolated for 13 percent of district-years that had missing irrigation data. Since this percentage is non-trivial, it is important to consider the robustness of the results to the missing data. In Appendix Table A8, I present results that exclude district-years that did not have irrigation information from the Land Use Statistics. As can be seen in the table, there are fewer households in the regression sample, so standard errors increase. However, the magnitude and statistical significance of the coefficients generally remain unchanged.

Figure 1: Histogram of the Dry Shock Variable



Notes: This figure shows the overall distribution of the dry shock variable. The median dry shock is 0.146 meters, while the 90th and 99th percentile are 0.379 meters and 0.715 meters, respectively.

Table 1: Summary Statistics on Rainfall

	Rainfall Level		Prop. of Districts	Dry Shock	
Year	Mean	SD	w/ Dry Shock	Mean	SD
2004	1.304	0.918	0.697	0.179	0.120
2005	1.362	0.782	0.574	0.174	0.137
2006	1.328	0.796	0.575	0.212	0.183
2007	1.438	0.944	0.480	0.128	0.106
2008	1.454	0.802	0.328	0.112	0.111
2009	1.208	0.785	0.794	0.222	0.151
2010	1.494	0.980	0.315	0.246	0.168
2011	1.377	0.721	0.359	0.235	0.307
2012	1.346	0.880	0.584	0.152	0.130

Notes: This table shows rainfall variation measured in meters per year. Column 1 indicates the years covered in the study. Columns 2 and 3 show the mean and standard deviation of annual rainfall across districts. Column 4 shows the proportion of districts in a given year that experience total rainfall below the long-term annual mean. The long-term mean is calculated over the 40-year period from 1973 to 2012. Columns 5 and 6 show the mean and standard deviation of the dry shock, defined as the absolute deviation of rainfall below the long-term mean. Gridded rainfall data come from Willmott and Matsuura (2015) and was aggregated to districts by taking the area-weighted average of all pixels that overlap with a given district.

Table 2: Summary Statistics for Household Food Consumption and Nutrition

Variable	Food Group	2004-05	2006-07	2007-08	2009-10	2011-12
Food Exp. (Rs.)	All categories	367.2 [168.5]	440.2 [205.3]	506.8 [231.2]	592.1 [264.7]	739.8 [336.6]
	Cereals	110.4 [42.4]	124.0 [50.4]	142.6 [54.9]	162.3 [72.5]	171.9 [77.4]
	Pulses, nuts, and oilseeds	24.0 [17.3]	33.6 [24.7]	34.4 [22.8]	45.8 [31.8]	55.5 [37.8]
	Vegetables and fruits	50.4 [30.5]	64.2 [37.1]	76.1 [44.4]	83.9 [50.3]	98.0 [59.5]
	Meat, fish, and dairy	81.4 [74.4]	99.0 [86.0]	122.5 [103.4]	138.2 [118.5]	190.5 [153.8]
	Sugar, honey, oils, and fats	44.9 [26.5]	48.5 [29.2]	50.5 [32.3]	66.0 [39.4]	83.8 [49.6]
	Processed food and beverages	53.8 [47.1]	67.9 [59.6]	78.0 [63.3]	92.4 [72.0]	135.8 [105.5]
Share in Food Exp.	Cereals	33.1 [12.5]	31.0 [12.4]	30.9 [11.6]	29.5 [12.2]	25.3 [11.0]
	Pulses, nuts, and oilseeds	6.7 [3.7]	7.6 [4.1]	7.0 [3.6]	7.9 [4.4]	7.7 [4.1]
	Vegetables and fruits	13.8 [4.9]	14.7 [5.0]	15.1 [5.2]	14.3 [5.5]	13.4 [5.3]
	Meat, fish, and dairy	19.5 [11.8]	20.2 [11.1]	21.6 [11.4]	21.0 [11.5]	23.5 [12.0]
	Sugar, honey, oils, and fats	12.6 [5.4]	11.4 [4.9]	10.2 [4.9]	11.5 [5.1]	11.8 [5.3]
	Processed food and beverages	14.0 [7.7]	14.8 [8.6]	14.9 [8.1]	15.4 [8.4]	18.0 [9.1]
Calories (kcal)	All categories	2159.2 [557.7]	2201.3 [608.7]	2259.8 [573.4]	2168.7 [546.1]	2239.4 [546.9]
	Cereals	1429.5 [384.0]	1415.7 [406.6]	1417.4 [377.6]	1366.6 [374.9]	1356.5 [362.8]
	Pulses, nuts, and oilseeds	103.9 [70.1]	116.3 [82.9]	110.7 [72.0]	103.1 [71.8]	119.9 [77.5]
	Vegetables and fruits	113.4 [68.8]	120.0 [72.6]	127.7 [71.9]	103.1 [60.0]	108.5 [61.5]
	Meat, fish, and dairy	168.2 [183.0]	180.6 [183.1]	206.7 [192.1]	176.9 [174.4]	187.7 [172.7]
	Sugar, honey, oils, and fats	266.4 [144.5]	283.7 [151.6]	270.2 [147.0]	293.2 [147.5]	317.6 [150.6]
	Processed food and beverages	60.9 [64.8]	71.0 [77.4]	113.1 [133.5]	117.0 [144.9]	141.8 [158.8]
Protein (gm)	All categories	58.2 [17.7]	58.7 [18.7]	61.9 [17.9]	57.4 [16.6]	59.6 [16.7]
	Cereals	37.6 [11.3]	36.3 [11.4]	37.7 [10.9]	36.0 [10.7]	35.8 [10.4]
	Pulses, nuts, and oilseeds	6.2 [3.8]	6.6 [4.2]	6.6 [3.9]	6.0 [3.7]	7.0 [4.0]
	Vegetables and fruits	3.2 [1.9]	3.3 [1.8]	3.5 [1.9]	2.9 [1.6]	2.9 [1.6]
	Meat, fish, and dairy	9.2 [8.4]	10.3 [8.9]	11.1 [8.8]	9.5 [7.8]	10.3 [7.9]
	Sugar, honey, oils, and fats	0.0 [0.0]	0.0 [0.0]	0.0 [0.0]	0.0 [0.0]	0.0 [0.0]
	Processed food and beverages	1.6 [1.5]	1.8 [1.8]	2.6 [2.8]	2.7 [3.1]	3.3 [3.4]
Fat (gm)	All categories	37.8 [21.6]	40.9 [22.8]	41.1 [22.9]	41.9 [21.5]	45.1 [21.9]
	Cereals	4.3 [2.8]	4.0 [2.7]	4.3 [2.7]	4.0 [2.3]	3.9 [2.1]
	Pulses, nuts, and oilseeds	2.0 [3.3]	2.8 [4.3]	2.1 [3.2]	2.1 [3.5]	2.4 [3.7]
	Vegetables and fruits	0.5 [0.3]	0.5 [0.3]	0.6 [0.3]	0.5 [0.3]	0.5 [0.3]
	Meat, fish, and dairy	10.9 [12.8]	11.5 [12.7]	13.5 [13.5]	11.5 [12.2]	12.1 [12.1]
	Sugar, honey, oils, and fats	17.9 [10.0]	19.7 [10.8]	17.6 [11.6]	21.1 [11.0]	22.9 [11.3]
	Processed food and beverages	1.8 [1.9]	2.0 [2.1]	2.6 [2.7]	2.6 [2.7]	3.1 [2.9]

Notes: This table reports mean (and in brackets, the standard deviation) of the following variables: food expenditure per capita per month (in Rupees, nominal), where food expenditure is defined as the value of food consumption and includes market purchases, home production, and in-kind transfers; budget share of each food group in total food expenditure; calories per capita per day (in kcal); protein per capita per day (in grams); and fat per capita per day (in grams). Data come from the NSS Consumer Expenditure Surveys. All values were winsorized at the top and bottom 1% within a given variable, round, and food group.

Table 3: Effects on Log Agricultural Yield

	Cereals		Pulses		Other Crops
	(1)	(2)	(3)	(4)	(5)
	Rice	Wheat	Gram	Urad	Potato
Dry shock	–0.261***	–0.197***	–0.237***	–0.094	–0.100*
	(0.052)	(0.039)	(0.060)	(0.062)	(0.058)
Year FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.109	0.231	0.086	0.085	0.057
Districts	539	478	483	472	463
Observations	4585	3982	3733	3696	3268

Notes: The dependent variable is ln(yield) at the district level, where yield is production (measured in tonnes) divided by area planted (measured in hectares). Dry shock is the absolute deviation of rainfall below the long-term mean (i.e., 1970-2012) in meters per year. The regressions control for irrigation, defined as the proportion of net sown area that is irrigated during each district-year. All regressions also include year-interacted district characteristics from the 2001 Census, namely, percent scheduled caste, percent literate, percent employed, and total population. Data on agricultural yields cover 2003-2012 and come from the Directorate of Economics and Statistics, Ministry of Agriculture. Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 4: Effects on Household Per Capita Food Consumption and Nutrition

	(1)	(2)	(3)	(4)	(5)
	Log Tot Exp	Log Food Exp	Log Calories	Log Protein	Log Fat
Dry shock	–0.060***	–0.068***	–0.048***	–0.050***	–0.095***
	(0.021)	(0.019)	(0.010)	(0.012)	(0.020)
Survey Round FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.441	0.448	0.154	0.143	0.158
Observations	288342	288342	288342	288342	288342

Notes: The dependent variables, indicated in the column titles, are expressed in natural log and are measured per capita per month at the household level. In Columns 1 and 2, expenditures include the value in Rupees of market purchases, home production, and in-kind transfers. Dry shock is the absolute deviation of rainfall (measured in the past 12 months prior to the household's survey month) below the district's long-term annual mean (i.e., from 1970-2012). All regressions include household characteristics, namely, dummies for religion, dummies social group (SC/ST/OBC), the fraction of household members in each male/female age cell (0-1, 1-3, 4-6, 7-9, 10-12, 13-15, 16-19, 20-39, 40-49, 50-59, 60-69, 70+), and the calendar month of the household's interview. In addition, the regressions control for irrigation (i.e., the proportion of net sown area that is irrigated in each district-year) and year-interacted district characteristics from the 2001 Census, namely percent scheduled caste, percent literate, percent employed, and total population. Data on household food consumption come from the NSS Consumer Expenditure Surveys, Rounds 60-64, 66, and 68 (January 2004- June 2008, July 2009-June 2010, July 2011-June 2012). Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 5: Effects on Household Non-Food Expenditure

	(1)	(2)	(3)	(4)	(5)
	Log Non-Food Exp	Log Clothing Exp	Log Durables Exp	Log Educ and Medical Exp	Log Fuel and Lighting Exp
Dry shock	–0.042*	–0.055*	–0.102	–0.178***	–0.051**
	(0.025)	(0.031)	(0.084)	(0.049)	(0.023)
Survey Round FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.371	0.366	0.388	0.561	0.399
Observations	288342	288342	288342	288342	288342

Notes: The dependent variables, indicated in the column titles, are expressed in natural log and are measured per capita at the household level. All expenditures include the value in Rupees of market purchases, home production, and in-kind transfers. Dry shock is the absolute deviation of rainfall (measured in the past 12 months prior to the household's survey month) below the district's long-term annual mean (i.e., from 1970- 2012). All regressions include household characteristics, namely, dummies for religion, dummies social group (SC/ST/OBC), the fraction of household members in each male/female age cell (0-1, 1-3, 4-6, 7-9, 10-12,13-15, 16-19, 20-39, 40-49, 50-59, 60-69, 70+), and the calendar month of the household's interview. In addition, the regressions control for irrigation (i.e., the proportion of net sown area that is irrigated in each district-year) and year-interacted district characteristics from the 2001 Census, namely percent scheduled caste, percent literate, percent employed, and total population. Data on household food consumption come from the NSS Consumer Expenditure Surveys, Rounds 60-64, 66, and 68 (January 2004-June 2008, July 2009-June 2010, July 2011-June 2012). Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 6: Effects on HH Per Capita Food Consumption and Nutrition, by Food Group

	Cereals	Pulses, nuts, and oilseeds	Vegetables and fruits	Meat, fish, and dairy	Sugar, honey, oils and fats	Processed food and beverages
Panel A: Log Food Expenditure Per Capita						
	(1)	(2)	(3)	(4)	(5)	(6)
Dry shock	–0.045**	–0.119***	–0.049	–0.087***	–0.078***	–0.085***
	(0.018)	(0.030)	(0.031)	(0.032)	(0.026)	(0.031)
Panel B: Log Calories Per Capita						
	(1)	(2)	(3)	(4)	(5)	(6)
Dry shock	–0.030***	–0.067**	–0.085***	–0.079*	–0.047**	–0.230***
	(0.011)	(0.031)	(0.032)	(0.041)	(0.021)	(0.050)
Panel C: Log Protein Per Capita						
	(1)	(2)	(3)	(4)	(5)	(6)
Dry shock	–0.029***	–0.075**	–0.093***	–0.089***	–0.020	–0.215***
	(0.011)	(0.033)	(0.031)	(0.031)	(0.029)	(0.055)
Panel D: Log Fat Per Capita						
	(1)	(2)	(3)	(4)	(5)	(6)
Dry shock	–0.014	–0.165***	–0.058*	–0.061	–0.082***	–0.360***
	(0.013)	(0.048)	(0.034)	(0.052)	(0.027)	(0.079)
Observations	288342	288342	288342	288342	288342	288342
Survey Round FEs	Yes	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables are expressed in natural logarithm and are measured per capita at the household level. In Panel A, food expenditures include the value in Rupees of market purchases, home production, and in-kind transfers. Dry shock is the absolute deviation of rainfall (measured in the past 12 months prior to the household's survey month) below the district's long-term annual mean (i.e., from 1970- 2012). All regressions include household characteristics, namely, dummies for religion, dummies social group (SC/ST/OBC), the fraction of household members in each male/female age cell (0-1, 1-3, 4-6, 7-9, 10-12, 13-15, 16-19, 20-39, 40-49, 50-59, 60-69, 70+), and the calendar month of the household's interview. In addition, the regressions control for irrigation (i.e., the proportion of net sown area that is irrigated in each district-year) and year-interacted district characteristics from the 2001 Census, namely percent scheduled caste, percent literate, percent employed, and total population. Data on household food consumption come from the NSS Consumer Expenditure Surveys, Rounds 60-64, 66, and 68 (January 2004-June 2008, July 2009-June 2010, July 2011-June 2012). Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 7: Effects on Log Prices, NSS Rural Price Collection Data

	Cereals		Pulses		Vegetables and Fruits		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Wheat	Rice	Gram	Urad	Potato	Spinach	Banana
Dry shock	0.024	0.021	0.016	–0.017	0.021	0.035	0.059
	(0.015)	(0.014)	(0.014)	(0.020)	(0.018)	(0.044)	(0.037)
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Market FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.910	0.889	0.800	0.950	0.698	0.524	0.682
# Markets	587	603	572	567	603	573	603
# Districts	367	373	361	357	373	361	373
Observations	4199	4699	4204	3914	4761	4205	4730

Notes: The dependent variable is ln(price) at the market-district level. Prices are in nominal terms and are based on the median retail price within each market-district-year. Dry shock is the absolute deviation of rainfall below the long-term mean (i.e., 1973-2012) in meters per year. The regressions control for irrigation, defined as the proportion of net sown area that is irrigated during each district-year. All regressions also include year-interacted district characteristics from the 2001 Census, namely, percent scheduled caste, percent literate, percent employed, and total population. Data on prices cover the years 2001-2006 and 2010-2011 and come from the NSS Rural Price Collection Survey. Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 8: Effects on Log Prices, Dept. of Consumer Affairs Data

	Cereals		Pulses		Vegetables
	Wheat	Rice	Gram Dal	Urad Dal	Potato
Panel A: Log Retail Prices, Full Sample					
	(1)	(2)	(3)	(4)	(5)
Dry shock	0.001	–0.001	–0.008	0.020	–0.038
	(0.021)	(0.026)	(0.019)	(0.026)	(0.032)
# Districts	97	99	99	99	99
Observations	3981	4562	4479	4339	4559
Panel B: Log Wholesale Prices, Full Sample					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.014	0.010	–0.025	0.021	–0.041
	(0.030)	(0.030)	(0.020)	(0.025)	(0.063)
# Districts	94	98	97	97	98
Observations	3790	4253	4215	4125	4254
Panel C: Log Retail Prices, Post-Monsoon Months					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.004	–0.022	–0.024	–0.006	–0.059
	(0.024)	(0.031)	(0.020)	(0.052)	(0.036)
# Districts	82	85	84	85	85
Observations	953	1088	1068	1031	1087
Panel D: Log Wholesale Prices, Post-Monsoon Months					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.087	–0.079	–0.093	–0.084	–0.099
	(0.081)	(0.064)	(0.064)	(0.066)	(0.071)
# Districts	80	83	82	83	83
Observations	911	1023	1009	988	1023
Month FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables are ln(retail price) in Panels A and C and ln(wholesale price) in Panels B and D at the district-month level. Prices are in nominal terms and are based on the average price in a given month from the district's main market. Panels A and B make use of the full sample, while Panels C and D restrict the sample to only those calendar months in the post-monsoon season (i.e., October-December). Dry shock is the absolute deviation of rainfall (measured in the past 12 months prior to the current month) below the long-term annual mean (i.e., 1973-2012) in meters per year. The regressions control for irrigation, defined as the proportion of net sown area that is irrigated during each district-year. All regressions also include year-interacted district characteristics from the 2001 Census, namely, percent scheduled caste, percent literate, percent employed, and total population. Data on prices cover January 2009 to June 2016 and come from the Department of Consumer Affairs, Price Monitoring Cell. Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 9: Effects on Employment and Earnings

	Proportion of Days Last Week			Log Ave Daily Earnings		
	(1) Employed	(2) Unemployed	(3) Not in LF	(4) All Activities	(5) Ag Activities	(6) Non-Ag Activities
Dry Shock	–0.015**	0.012***	0.004	–0.076***	–0.080***	–0.072**
	(0.008)	(0.004)	(0.008)	(0.024)	(0.026)	(0.032)
Survey Round FEs	Yes	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.375	0.036	0.401	0.407	0.540	0.356
Observations	1041678	1041678	1041678	233349	96910	138310

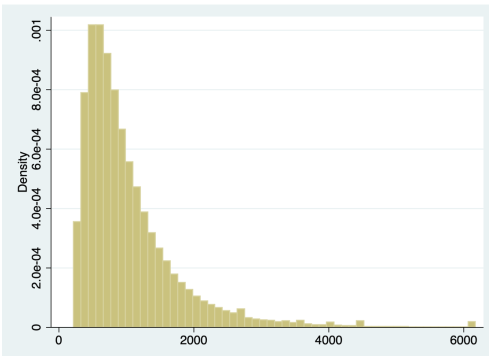
Notes: All dependent variables are measured at the individual level. In the first three columns, the dependent variable is the proportion of days in the last week that the household member spent employed, unemployed, or not in the labor force (LF). The dependent variable in the last three columns, log daily earnings, is the natural log of earnings per day worked for individuals who report working as a casual laborer or as a regular wage employee, winsorized at the top and bottom 1% within each survey round. The dependent variable in the penultimate column is based on earnings and number of days worked in agricultural activities only, while in the final column, it is based on work in non-agricultural activities only. Dry shock is the absolute deviation of total rainfall (measured in the past 12 months prior to the household's survey month) from the district's long-term mean of annual precipitation (i.e., from 1970-2012). All regressions include individual characteristics, namely, gender, dummies for age group, literacy, dummies for social group (SC/ST/OBC), dummies for religion, dummies for marital status, and the calendar month of the household's interview. In addition, the regressions control for irrigation (i.e., the proportion of net sown area that is irrigated in each district-year) and year-interacted district characteristics from the 2001 Census, namely, percent scheduled caste, percent literate, percent employed, and total population. Data on employment variables come from the NSS Employment and Unemployment Surveys, Rounds 60-62, 64, 66, and 68 (January 2004-June 2006, July 2007-June 2008, July 2009-June 2010, July 2011- June 2012), restricted to individuals aged 15-59. Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Table 10: Heterogeneity of Effects

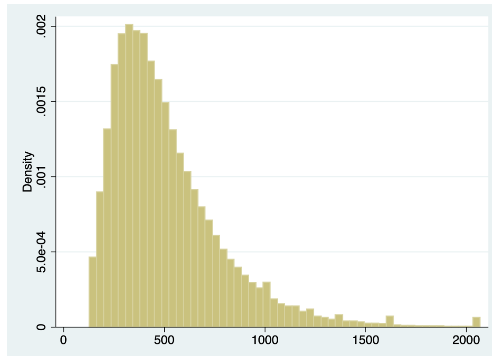
	Log Tot Exp	Log Food Exp	Log Calories	Log Protein	Log Fat
Panel A: By Gender of Household Head					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.061***	–0.068***	–0.046***	–0.049***	–0.089***
	(0.021)	(0.019)	(0.010)	(0.012)	(0.020)
Dry shock ∗ **1**(Female head)	0.007	0.002	–0.015	–0.006	–0.043**
	(0.020)	(0.019)	(0.010)	(0.011)	(0.018)
Panel B: By Season					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.054**	–0.065***	–0.032***	–0.040***	–0.092***
	(0.023)	(0.020)	(0.012)	(0.013)	(0.025)
Dry shock ∗ **1**(Cropping season)	–0.008	–0.004	–0.022**	–0.013	–0.003
	(0.017)	(0.017)	(0.010)	(0.010)	(0.023)
Panel C: By Past Dry Shock					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.080***	–0.093***	–0.062***	–0.066***	–0.115***
	(0.029)	(0.026)	(0.013)	(0.015)	(0.024)
Dry shock ∗ **1**(Dry $\text{shock}_{t-1} > 0$)	0.038	0.053**	0.031*	0.036**	0.052*
	(0.030)	(0.025)	(0.016)	(0.017)	(0.028)
Observations	288342	288342	288342	288342	288342
Survey Round FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes

Notes: The dependent variables, indicated in the column titles, are expressed in natural log and are measured per capita per month at the household level. In Columns 1 and 2, expenditures include the value in Rupees of market purchases, home production, and in-kind transfers. Dry shock is the absolute deviation of rainfall (measured in the past 12 months prior to the household's survey month) below the district's long-term annual mean (i.e., from 1970-2012). In Panel A, **1**(Female head) is an indicator variable indicating a female household head. In Panel B, **1**(Cropping season) is an indicator variable for whether the household was interviewed during the calendar months June to February, which correspond roughly to the *kharif* and *rabi* cropping seasons. In Panel C, **1**(Dry $\text{shock}_{t-1} > 0$) is an indicator for whether the one-year lagged dry shock variable is positive. All regressions include household characteristics, namely, dummies for religion, dummies social group (SC/ST/OBC), the fraction of household members in each male/female age cell (0-1, 1-3, 4-6, 7-9, 10-12, 13-15, 16-19, 20-39, 40-49, 50-59, 60-69, 70+), and the calendar month of the household's interview. In addition, the regressions control for irrigation (i.e., the proportion of net sown area that is irrigated in each district-year) and year-interacted district characteristics from the 2001 Census, namely percent scheduled caste, percent literate, percent employed, and total population. Data on household food consumption come from the NSS Consumer Expenditure Surveys, Rounds 60-64, 66, and 68 (January 2004-June 2008, July 2009-June 2010, July 2011-June 2012). Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

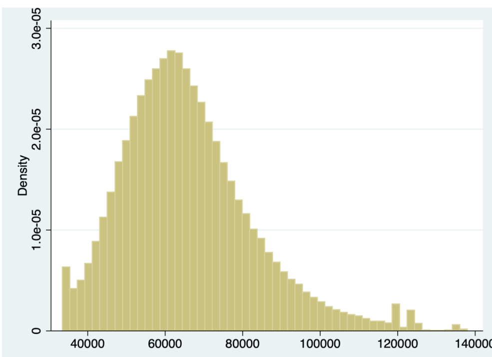
Appendix Figure A1:
Monthly Per Capita Expenditures and Macronutrient Consumption



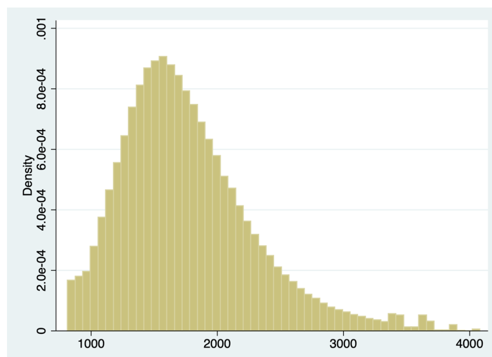
(a) Total Expenditure (Rs.)



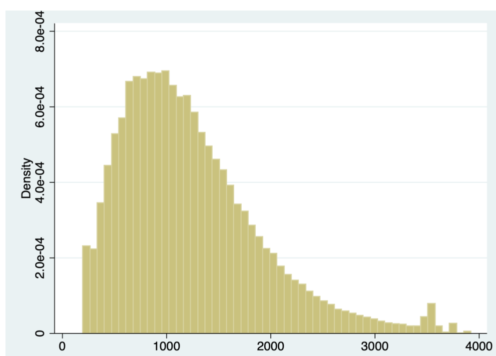
(b) Food Expenditure (Rs.)



(c) Calories (kcal)



(d) Protein (mg)



(e) Fat (mg)

Notes: This figure shows the distribution of household food consumption and nutrition outcomes, expressed in monthly per capita values. As can be seen in the above histograms, the variables are approximately log normally distributed.

Appendix Table A1: Robustness Check with Temperature Controls

	(1) Log Tot Exp	(2) Log Food Exp	(3) Log Calories	(4) Log Protein	(5) Log Fat
Dry shock	–0.058***	–0.070***	–0.048***	–0.051***	–0.103***
	(0.022)	(0.020)	(0.010)	(0.012)	(0.020)
Survey Round FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.441	0.448	0.154	0.143	0.158
Observations	288342	288342	288342	288342	288342

Notes: These regressions replicate Table 4 but include temperature in the control variables as a robustness check. The temperature variable is defined as the average monthly temperature over the last 12 months prior to the household's survey month. Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Appendix Table A2: Robustness Check with Alternative Rainfall Data

	(1) Log Tot Exp	(2) Log Food Exp	(3) Log Calories	(4) Log Protein	(5) Log Fat
Dry shock	–0.035*	–0.043**	–0.027**	–0.025*	–0.038*
	(0.020)	(0.018)	(0.013)	(0.014)	(0.020)
Survey Round FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.441	0.448	0.154	0.142	0.157
Observations	288750	288750	288750	288750	288750

Notes: These regressions replicate Table 4 but use the CRU dataset as an alternative source of rainfall data. Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Appendix Table A3: Robustness Check with Alternative Dry Shock Definitions

	Log Tot Exp	Log Food Exp	Log Calories	Log Protein	Log Fat
	Panel A: Standardized Dry Shock				
	(1)	(2)	(3)	(4)	(5)
Standardized Dry Shock	–0.017***	–0.019***	–0.011***	–0.011***	–0.011**
	(0.006)	(0.005)	(0.003)	(0.004)	(0.005)
	Panel B: Rainfall Below 20^{th} Percentile				
	(1)	(2)	(3)	(4)	(5)
1(Rainfall < 20^{th} Pctile)	–0.018***	–0.019***	–0.010***	–0.010***	–0.017***
	(0.005)	(0.004)	(0.003)	(0.003)	(0.005)
Survey Round FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.441	0.448	0.154	0.143	0.157
Observations	288342	288342	288342	288342	288342

Notes: These regressions replicate Table 4 but use alternative definitions for a dry shock. Standardized dry shock is the absolute deviation of annual rainfall from its long-term mean divided by its standard deviation. **1**(Rainfall < 20^{th} Percentile) is a dummy variable for rainfall below the 20th percentile within the district over the period 1973-2012. Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Appendix Table A4: Robustness Check for Intensity of Rainfall Shocks

	(1) Log Tot Exp	(2) Log Food Exp	(3) Log Calories	(4) Log Protein	(5) Log Fat
Dry shock: > 1.75 SD below	0.007	0.010	–0.039***	–0.049***	–0.029
	(0.046)	(0.040)	(0.012)	(0.012)	(0.018)
Dry shock: 1.25-1.75 SD below	0.008	0.014	–0.020***	–0.024***	0.007
	(0.033)	(0.028)	(0.006)	(0.006)	(0.011)
Dry shock: 0.75-1.25 SD below	–0.048**	–0.036**	–0.011***	–0.014***	–0.012
	(0.019)	(0.016)	(0.004)	(0.005)	(0.007)
Dry shock: 0.25-0.75 SD below	–0.060***	–0.050***	–0.007**	–0.008**	–0.003
	(0.016)	(0.015)	(0.003)	(0.004)	(0.007)
Wet shock: 0.25-0.75 SD above	0.046**	0.041**	0.007**	0.005	0.023***
	(0.018)	(0.016)	(0.003)	(0.004)	(0.007)
Wet shock: 0.75-1.25 SD above	0.072***	0.056***	0.011**	0.012**	0.038***
	(0.022)	(0.019)	(0.004)	(0.005)	(0.009)
Wet shock: 1.25-1.75 SD above	0.076**	0.057**	0.006	0.005	0.036***
	(0.031)	(0.027)	(0.007)	(0.008)	(0.013)
Wet shock: > 1.75 SD above	0.103***	0.076***	0.018***	0.023***	0.045***
	(0.026)	(0.024)	(0.007)	(0.008)	(0.012)
Survey Round FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.008	0.007	0.001	0.002	0.001
Observations	288412	288412	288412	288412	288412

Notes: The independent variables are dummies representing bins of the standardized rainfall measure. Each bin is 0.5 standard deviations wide, and the bin centered at 0 is the omitted category. Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Appendix Table A5: Robustness Check with Spatially Correlated Errors

	Log Tot Exp	Log Food Exp	Log Calories	Log Protein	Log Fat
Panel A: Temporal lag of 0 year, Spatial lag of 100 km					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.060***	–0.068***	–0.048***	–0.050***	–0.095***
	(0.019)	(0.010)	(0.013)	(0.014)	(0.023)
Panel B: Temporal lag of 0 year, Spatial lag of 200 km					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.060***	–0.068***	–0.048***	–0.050***	–0.095***
	(0.021)	(0.021)	(0.012)	(0.013)	(0.024)
Panel C: Temporal lag of 1 year, Spatial lag of 100 km					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.060***	–0.068***	–0.048***	–0.050***	–0.095***
	(0.019)	(0.019)	(0.013)	(0.014)	(0.023)
Panel D: Temporal lag of 1 year, Spatial lag of 200 km					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.060***	–0.068***	–0.048***	–0.050***	–0.095***
	(0.021)	(0.021)	(0.012)	(0.013)	(0.024)
Panel E: Temporal lag of 2 years, Spatial lag of 100 km					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.060***	–0.068***	–0.048***	–0.050***	–0.095***
	(0.019)	(0.019)	(0.013)	(0.014)	(0.023)
Panel F: Temporal lag of 2 years, Spatial lag of 200 km					
	(1)	(2)	(3)	(4)	(5)
Dry shock	–0.060***	–0.068***	–0.048***	–0.050***	–0.095***
	(0.021)	(0.021)	(0.012)	(0.013)	(0.024)
Survey Round FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Observations	288342	288342	288342	288342	288342

Notes: These regressions replicate Table 4 but use spatially correlated errors following Conley (1999), with a temporal lag of 0, 1, or 2 years and a spatial lag of 100 or 200 kilometers. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Appendix Table A6: Robustness Check with Outcomes in Levels

	(1) Tot Exp (Rs.)	(2) Food Exp (Rs.)	(3) Calories (kcal)	(4) Protein (mg)	(5) Fat (mg)
Dry shock	–24.916	–9.594	–2937.036***	–81.649***	–95.253***
	(26.740)	(10.299)	(647.824)	(19.685)	(18.157)
Survey Round FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.321	0.387	0.143	0.135	0.153
Observations	288342	288342	288342	288342	288342

Notes: These regressions replicate Table 4 but use outcomes measured in levels (expressed as monthly per capita values) rather than log. Standard errors are clustered at the district level. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Appendix Table A7: Robustness Check with Flexible Intercept

	(1) Log Tot Exp	(2) Log Food Exp	(3) Log Calories	(4) Log Protein	(5) Log Fat
Dry shock	–0.073***	–0.079***	–0.052***	–0.059***	–0.128***
	(0.026)	(0.024)	(0.011)	(0.013)	(0.023)
Survey Round FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.441	0.449	0.154	0.143	0.158
Observations	288342	288342	288342	288342	288342

Notes: These regressions replicate Table 4 but include an additional control variable, D_{it}, to allow the intercept to differ between positive and negative rainfall shocks. D_{it} is an indicator variable for rainfall below the long-term average. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

Appendix Table A8: Robustness Check with Missing Irrigation

	(1) Log Tot Exp	(2) Log Food Exp	(3) Log Calories	(4) Log Protein	(5) Log Fat
Dry shock	–0.047**	–0.054**	–0.051***	–0.055***	–0.107***
	(0.024)	(0.022)	(0.011)	(0.013)	(0.022)
Survey Round FEs	Yes	Yes	Yes	Yes	Yes
District FEs	Yes	Yes	Yes	Yes	Yes
Controls	Yes	Yes	Yes	Yes	Yes
Adj. R-squared	0.436	0.439	0.163	0.152	0.162
Observations	243603	243603	243603	243603	243603

Notes: These regressions replicate Table 4 but exclude district-years with missing irrigation, as these missing data was linearly interpolated and extrapolated in the previous table. *** indicates statistical significance at the 1% level, ** at the 5% level, and * at the 10% level.

[1] For example, see Dai (2013) on increasing drought under global warming and Parry, Rosenzweig, Iglesias, Livermore, and Fischer (2004) on climate change and global food production.

[2] Table 1 illustrates rainfall variability in India from 2004 to 2012 and is discussed further in Section 3.

[3] Although the NSS operations manual indicates that different villages within each district are to be surveyed throughout the year, this system is not strictly enforced in areas with arduous field conditions (e.g., Andaman and Nicobar Islands).

[4] Note that the adjustment factor is greater than one for households that are receiving meals away from home much more than giving meals to others. Similarly, it is less than one for households that are serving many more meals to non-household members than receiving meals away from home. In the empirical analysis, I drop all households with adjustment factors greater than 2 and less than 0.5 in the empirical analysis. These households correspond to those with adjustment factors well below and well above the 1st and 99th percentiles, respectively.

[5] While the median allows me to obtain a value that is not sensitive to outliers, it may not fully represent the potential consequences of a drought. For instance, if the impact of a negative rainfall shock is short-lived or does not shift the distribution of prices, then the drought effects I observe will be biased toward zero.

[6] The data are publicly available at https://fcainfoweb.nic.in/reports/report_menu_web.aspx.

[7] The data are publicly available at https://aps.dac.gov.in/LUS/Public/Reports.aspx.

[8]These categories of food, as well as the composition of each food category, comes from various NSS publications (see NSS, 2001, 2007, 2012, 2014b). Note that the category "Pulses, Nuts, and Oilseeds" contain oilseeds such as soybean and groundnut that are consumed directly rather than processed into oils. Oilseeds that are purchased or grown for extracting edible oil for cooking are counted in the "Sugar, Honey, Oils, and Fats" category.

[9] The summary statistics in Table 2 also echo the well-known calorie consumption puzzle in India: incomes have increased over time, but average calorie intake has remained stable. A number of different

explanations have been proposed such as lower levels of physical activity (e.g., Deaton & Drèze, 2009), improvements in the health and disease environment (e.g., Duh & Spears, 2016), household food budget squeeze (e.g., Basole & Basu, 2015), and underreporting of calories due to meals taken away from home (e.g., Smith, 2015).

[10] In the robustness checks I also examine the impact of a wet shock on household food consumption and nutritional intake. The results show that wet shocks are associated with positive effects, suggesting that food security is a much more pressing and relevant issue during a dry shock.

[11] Note that markets are smaller geographic units than districts.

[12] Following various NSS publications (e.g., NSS, 2001, 2007, 2012, 2014b), I use the following age bins: 0–1, 2–3, 4–6, 7–9, 10–12, 13–15, 16–19, 20–39, 40–49, 50–59, 60–69, and 70+.

[13] Mahajan (2017) shows that during a drought—defined as rainfall below the 20th percentile for a district—rice and wheat yields decline by 8.7 and 5.7 percent. Although my definition of a dry shock differs from Mahajan (2017) in that I use the absolute deviation of rainfall below the long-term mean, I find effects of the same order: during a dry shock of 0.3 meters—the average dry shock when rainfall is below the first quintile—agricultural yields fall by 7.8 percent for rice and 5.9 percent for wheat (Table 3).

[14] To estimate the Conley (1999) spatially correlated errors, I use the implementation by Hsiang (2010).