The Gendered Effects of Climate Change: Production Shocks and Labor Response in Agriculture*

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Abstract

Climate change has increased rainfall uncertainty, leading to greater production risks in agriculture. We examine the gender-differentiated labor impacts of droughts resulting from lower precipitation using unique individual-level panel data for agricultural households in India over half a decade. Accounting for unobserved heterogeneity in individual responses, we find that women's workdays fall by 11% more than men's when a drought occurs, driven by former's lack of diversification to the non-farm sector. Women are less likely to work outside their village and migrate relative to men in response to droughts, and are consequently unable to cope fully with the adverse agricultural productivity shock. Our findings can be explained by social costs emanating from gender norms that constrain women's access to non-farm work opportunities. The results highlight the gendered impact of climate change, potentially exacerbating extant gender gaps in the labor market.

JEL classification: Q54, J16, J43, J60

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1 Introduction

Climate change has not only resulted in a rise in average temperatures, it has also increased the incidence of extreme weather events. The frequency of droughts and floods has risen and is predicted to rise further if climate change continues unabated. Amongst all economic sectors, agriculture is likely to face the greatest brunt of increasing rainfall uncertainty since more than 75% of the world's cropped area is rain-fed (Pachauri *et al.* , 2014). Rising climatic uncertainty is, thus, likely to make agricultural incomes and employment prone to productivity risks - a greater concern in developing countries where agricultural systems are largely rain-fed and are also managed by some of the poorest communities. The absence of social insurance and incomplete credit markets in low-income economies underlies the importance of labor as a resource for individuals to cope with such shocks. However, climate change can potentially exacerbate extant gender differences in labor market outcomes when women's access to off-farm work opportunities are constrained by social factors.

In this paper we use high frequency, individual-level panel data capturing seasonal labor supply during 2010-14 across eight agro-climatic zones of India to analyse the role of labor markets in mitigating the impact of adverse agricultural production shocks due to deficient rainfall. Specifically, we examine the impact of droughts on individuals' overall labor force participation, employment on the farm and diversification towards the non-farm sector on both the extensive and intensive margins. In a context where men are often better placed to take advantage of available coping mechanisms, we analyse these labor responses by gender. We, thus, extend the existing literature to investigating gender differences in labor market response to smooth out risks emanating from potentially sustained productivity shocks due to climate change in predominantly agrarian economies.

Our results indicate that the fall in labor force participation, in the event of a drought, is significantly larger for women relative to men. Women are 7.1% less likely to be employed than men but 82.5% more likely to seek work in a drought year. On the intensive margin, women witness a greater reduction in days of employment in comparison to men by 11%.

At the same time, they spend 15.4% more days seeking work, relative to men, when faced with a drought shock. Moreover, while men increase days spent on non-farm work by 12.4%, there is no significant impact on women's engagement in the non-farm sector. Consequently, women's non-farm workdays relative to men's fall by 10.9% in drought years. Hence, while men diversify to non-farm sector jobs to cope with droughts, women do not, even as they seek work and their real farm wage earnings (conditional on being employed on the farm) fall by 29%.

We find that the lack of substitution towards the non-farm sector in response to a drought by women is due to their restricted mobility. Women are less likely than men to work outside the village or migrate, on average, and more so in drought years. The probability that men take up work outside the village and migrate during a drought increases by 1.6 percentage points (pp) and 0.8 pp, respectively, but there is no impact on women's workplace location. Men's higher mobility translates into 18.2% greater non-farm earnings for them relative to women, in the event of a drought.

Our findings can be explained by social costs emanating from rigid gender norms that place a higher burden of home production and care work on women, as well as on women's sexual 'purity' that inhibit their access to alternative sources of employment beyond their immediate vicinity. Not surprisingly, our analysis shows that women who are younger, married and with young children are not only less likely to substitute their labor to the non-farm sector, they are also less likely to migrate relative to men with the same characteristics. We do not find evidence in support of gender skill differentials or safety concerns as an explanation for women's lack of off-farm diversification. These findings are robust to individuals' unobserved heterogeneity, seasonality, secular and village specific trends. They are also held up by nationally representative district-level panel data.

The existing literature has largely focused on the agricultural productivity effects of rainfall shocks measured by crop yield and income of farm households across developing and developed countries.[1] However, effects of rainfall shocks on household consumption have largely been found to be muted, thus pointing towards consumption smoothing by households (Jacoby & Skoufias, 1998; Kurosaki, 2015). Since the reliance on insurance is almost absent and credit markets are incomplete (Morduch, 1995), utilization of labor, specifically diversification to the non-farm sector has been well documented as a coping strategy adopted by agricultural households in developing countries for economic shocks (Rose, 2001; Colmer, 2018; Grabrucker & Grimm, 2020; Blakeslee *et al.* , 2020).[2] Studies also document a fall in real daily farm wages due to reduction in demand for labor during a drought, with a larger wage reduction in areas with lower access to non-farm opportunities (Jayachandran, 2006; Auffhammer *et al.* , 2012). Naturally, households often migrate when incomes and livelihoods are adversely affected due to weather shocks like deficient rainfall (See Badiani & Safir (2008); Minale (2018); Morten (2019), among others), floods (Giannelli & Canessa, 2021) and storms (Gröger & Zylberberg, 2016).[3]

While the literature on aggregate household labor response to climate shocks is rich, much less is known about the individual, specifically gender-differentiated responses to these shocks.[4] In the context of developing countries where women are generally less mobile and less likely to search widely for work (Heath & Mobarak, 2015; Andrabi *et al.* , 2013), men may be better placed to cope with productivity shocks in agriculture and diversify into sectors less

[1] Yang & Choi (2007) for the Philippines, Fishman (2011) for India and Burke & Emerick (2016) for the United States, to name a few. See Dell *et al.* (2014) for a complete review of studies that look at effects of precipitation and temperature shocks on agricultural yield and productivity as well as adaptation by farmers.

[2] Absent this labor reallocation, the economic losses can be enormous – up to 69% higher as estimated by Colmer (2018) for temperature-driven adjustments using data from Indian firms. Other coping mechanisms include – diversifying income sources to the non-farm sector (Ito & Kurosaki, 2009); ex-ante cultivating low risk crops (Morduch, 1995); varying planting timing (Kala, 2017); investing in increased irrigation (Taraz, 2017) and using drought-resistant seeds - these strategies are however often more costly and less likely to be adopted in developing countries (Kristjanson *et al.* , 2017).

[3] Not all types of aggregate income shocks lead to increased migration though. For instance, Halliday (2012) finds reduced migration in response to earthquakes in El Salvador.

[4] There is, however, a significantly larger literature on the effect of low rainfall on a range of other gendered outcomes – health (Neumayer & Plümper, 2007; Deschênes *et al.* , 2009), schooling (Shah & Steinberg, 2017), crime (Sekhri & Storeygard, 2014), loss of assets (Rakib & Matz, 2016) and lower human capital accumulation (Zimmermann, 2012) of females, among others. In contrast, in the context of labor markets, the literature is scant. For instance, Mahajan (2017) finds evidence of gender-differentiated wage impacts in response to weather-related rainfall shocks, in rainfed rice cultivating areas of India.

subject to weather shocks. But evidence on gender differences in labor response for smoothing the risk emanating from climate shocks, is almost absent, with a few exceptions. In Uganda, where men and women cultivate separate plots of land, Agamile *et al.* (2021) show that women diversify to more risky, commercial crops and away from subsistence farming as men allocate more time to off-farm labor employment during a drought. Maitra & Tagat (2019) examine the gender-differential in the labor responses for self-employed and wage work at the aggregate, district level in India and find that men increase regular wage work in response to negative rainfall shocks while there is no change for women. None of these papers addresses either individual or household level unobserved heterogeneity in assessing the response to climate shocks.[5]

In contrast to the existing literature's focus on household diversification, our study provides the most consistent estimates to-date of individual men's and women's labor response to climate shocks by accounting for unobserved individual heterogeneity. Moreover, while the existing literature focuses on how households diversify their income sources when farm productivity shrinks, we focus on the gender differences in individual decisions when struck by an adverse productivity shock. Second, and relatedly, unlike the aggregate geographical data used in previous studies, we underline the potential gender-differentiated impact of persistent climate shocks utilizing novel individual-level panel data over eight agro-climatic zones, collected at monthly frequency. We are thus able to account for seasonal impacts that are relevant for the agricultural sector.

Further, our analysis uncovers the underlying mechanisms that can explain the lower likelihood of women substituting towards less risky, non-farm sector jobs, relative to men through detailed data on the nature of employment, place of work and migration. Unlike most household surveys that capture employment details of only current members of the household and miss out on those members who are temporary migrants, our data allow us to

[5] Kochar (1999) finds evidence for consumption smoothing by cultivating households in the event of household crop income shocks (as opposed to an aggregate shock, such as rainfall) through diversification of labor to the non-farm sector, but only by men. Due to data constraints, she does not delve into either the mechanisms that cause this gendered response, in general, or the location of non-farm work, specifically.

investigate coping mechanisms from farm income losses through engagement in migrant work, and the extent to which men and women are able to access non-farm sources of employment. Our research, thus, also speaks to the literature on migration, by highlighting the role of seasonal migration as a coping mechanism and potentially in addressing the long-term impact of climate change on gender equality.[6] As opposed to the theoretical prediction and empirical evidence that women's employment rate increases in response to negative household level idiosyncratic income shocks in low-income economies (Attanasio *et al.* , 2005; Skoufias & Parker, 2006; Sabarwal *et al.* , 2011), we show that while women are more likely to seek work due to negative aggregate income shocks, their employment may not actually increase if their labor mobility is limited. Indeed, we find suggestive evidence that public employment programs that provide work close to home, such as the National Rural Employment Guarantee Scheme (NREGS) in India, not only mitigate production risks in agriculture in the short-run but also stem gender disparities in employment opportunities.

The remainder of the paper is organized as follows. In the next section, we set up the conceptual framework. Section 3 describes the data used in the analysis and discusses the estimation strategy. The results and their robustness are presented in Section 4. We discuss the mechanisms that underlie our findings in Section 5, and conclude in Section 6.

2 Conceptual Framework

We develop a simple theoretical framework for analysing labor supply decisions in response to production shocks in an agrarian economy. Assume two sectors - farm (a) and non-farm (n), and two types of agents (g) - female (f) and male (m). A representative agent is endowed with one unit of time that can be allocated to three activities: farm work (l_a), non-farm work (l_n) and leisure ($1 - l_a - l_n$). The agent obtains utility from consumption of farm good (c_a), non-farm good (c_n) and leisure ($1 - l_a - l_n$) and takes prices and wages as given.

[6] Halliday (2012) finds some evidence of male migration in El Salvador when harvest or livestock losses occur but no gender differences in migratory response to such shocks, while there is a decline in the probability of migration following shocks like earthquakes.

We build on the empirical evidence around restricted labor mobility of women by including social costs associated with an agent working in the non-farm sector in our framework. Agents internalise these social costs, deriving disutility from participation in the non-farm sector, which varies by gender, with women bearing a higher disutility. To elaborate, while farm work is usually close to home in agrarian economies, non-farm work is typically located at a distance. In our data, for instance, the average distance to farm work (conditional on farm employment) in a month, including seasonal migration, is 68 km while it is 3846 km to non-farm work (conditional on non-farm employment), indicating the role of seasonal migration for latter jobs. Thus, social costs can arise due to the stigma associated with women's participation in work that reduces their time at home – a consequence of social norms around the gendered division of labor at home wherein women are expected to be primary caregivers (Afridi *et al.* , 2019).[7] In addition, notions about women's sexual 'purity' can cause stigma if women are likely to interact with men (other than family members) while travelling to work or at work (Dean & Jayachandran, 2019; Eswaran *et al.* , 2013). As we discuss later, non-farm work is predominantly male-dominated in India.

The utility maximization problem for an agent, can thus, be given by:

$$\max_{c_a, c_n, l_a, l_n} \; U_g = u_g\left(c_a, c_n, 1 - l_a - l_n\right) - v_g\left(l_n\right) \tag{1}$$

subject to,

$$c_a + c_n p \leq l_a w_a + l_n w_n \tag{2}$$

where $v_g\left(l_n\right)$ captures dis-utility due to the social cost of participation in the non-farm sector. The utility function is assumed to be well behaved, i.e. increasing at a decreasing rate in all

[7] Across the world, women spend triple the time on unpaid care work than men, ranging from 1.5-2.2 in North America and Europe to 6-6.8 times in Middle East-North Africa and South Asia (OECD Report). Time Use Survey for India (2018-19) shows that women spend eight times more time on household and care work than men (Hindustan Times). Further, in a recent survey by the PEW center, around 40% respondents in India reportedly prefer a marriage in which the husband provides for the family and the wife takes care of home and children as compared to 23% across the 34 countries surveyed in 2019. Among other low-middle income countries - Philippines, Kenya and Nigeria - this proportion stood at 32%, 20% and 33%, respectively.

the arguments. The price of the farm good is normalised to one, while p denotes the price of the non-farm good. w_a and w_n are the wage rates in the farm and the non-farm sector, respectively, with the assumption that $w_a < w_n$. We consider the extreme case where only women face dis-utility from working in the non-farm sector.[8]

On the production side, the farm production function is given by:

$$A = \theta B^{\epsilon} L_a^{1-\epsilon} - L_a w_a \tag{3}$$

where θ is the productivity parameter, B denotes the land used in production, L_a is total labor employed in farm and ϵ is the share parameter.[9]

A negative productivity shock to the farm sector is denoted by D, specifically drought, that reduces the profit maximising equilibrium labor demand ($L_a = \left(\frac{\theta B^{\epsilon} - \theta\epsilon B^{\epsilon}}{w_a}\right)^{1/\epsilon}$) and as a consequence depresses wage rates ($\frac{dw_a}{dD} < 0$). We assume that production in the non-farm sector is independent of negative agricultural productivity shocks such as a drought.[10]

The solution to the utility maximization problem gives us the labor supply responses during a productivity shock to the farm sector (see Appendix for details). We are interested in the gender gap in these responses, which are expressed as follows:

$$\frac{dl_{af}}{dD} - \frac{dl_{am}}{dD} = \left(\frac{R+S}{H+Z} - \frac{R}{H}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{4}$$

$$\frac{dl_{nf}}{dD} - \frac{dl_{nm}}{dD} = \left(\frac{J}{H+Z} - \frac{J}{H}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{5}$$

The terms H, R, S, J and Z are a set of double derivatives of the utility function and

[8]We find similar results if we instead assume that both the sexes incur this cost with women bearing a higher cost.

[9]We assume only one type of labor in this simple theoretical exposition, i.e., male and female labor are perfect substitutes. This implies that both types of labor get the same wage rate (w_a). This assumption is only for simplification of the theoretical exposition. We find similar results, albeit under some additional assumptions, when using a production function where male and female labor are imperfect substitutes.

[10]Again, this assumption is only for simplification of the theoretical exposition. In fact, as long as the effect of drought on the productivity in the non-farm sector is smaller than its effect on the farm sector, an assumption validated by evidence that climate shocks affect the farm sector more (Pachauri *et al.* , 2014), our theoretical predictions go through.

are defined in the Appendix. One can sign these expressions under certain parametric assumptions. All plausible cases under which women's diversification to the non-farm sector employment could be restricted, while men move to the non-farm sector, when a drought occurs, are discussed in the Appendix. For simplicity of exposition, here we discuss the case when $H>0$. Under this case, $R<0$ and $J>0$, which implies that $\frac{dl_{am}}{dD} < 0$ and $\frac{dl_{nm}}{dD} > 0$, i.e. men diversify from the farm to the non-farm sector during a drought. The corresponding sign for female farm labor supply ($\frac{dl_{af}}{dD}$) depends on the values of S and Z which are associated with the social costs. While the sign of Z depends on the shape of the dis-utility function, the direction of S is ambiguous. Therefore, the direction of change in farm work for women in response to a drought can be either negative or positive, depending on the relative magnitude of these terms. This makes the relative effect of drought on women's versus men's farm labor employment ambiguous in equation (4).

Next, we look at the relative effect of drought on non-farm labor response by women versus men in equation (5). Given $H>0$, the sign of this term depends only on the sign of Z —when Z is positive, i.e., for a convex dis-utility function, the increase in the non-farm workdays of women would be less than that of men when faced with a drought shock. In this case, the relative effect of drought on women's versus men's non-farm labor employment is negative in equation (5), i.e. women are less likely to increase supply to the non-farm sector in the event of a drought when compared to men.

Hence, dis-utility from participation in work located further away due to social costs can restrict women's labor mobility and diversification away from the more risky farm sector. Women's limited mobility can, therefore, lead to gendered effects in labor response to climate shocks.

3 Data and Methodology

We now describe the data and variables used in empirically validating our hypothesis above.

3.1 Data

3.1.1 Individual labor market outcomes

We use five rounds of the Village Dynamics in South Asia (VDSA) longitudinal survey data collected by ICRISAT in India.[11] The VDSA study aims to understand the dynamics of agricultural development and rural poverty by following households in 30 villages (representative of the Semi-Arid Tropics (SAT) and Humid Tropics regions) across eight states of India.[12] Figure 1 shows the location of the sampled villages, which cover eight of the twenty agro-climatic zones of India. Each round collects employment data for the entire agricultural year, i.e. from July to June of the following year, for 40 households per village, at a monthly frequency. These households (30 cultivator and 10 landless households) are selected at the beginning of the survey through stratified random sampling based on operational landholding size.[13] Detailed information on sampled households' socio-economic characteristics, agricultural production and livelihoods are collected annually, at the beginning of each agricultural year (July).

The survey records employment-related details for every month of each year for each member of a sampled household, including temporary migrants.[14] We use data on all individuals aged 15 and above in the five latest rounds of the survey from 2010-2014.[15] We, thus, use an individual-level monthly employment panel, allowing us to account for the individual-level unobserved heterogeneity. Our sample consists of 5,931 individuals from 1,367 households, comprising a total of 278,971 individual-month year observations (see Table

[11] For details see http://vdsa.icrisat.ac.in/.

[12] The SAT regions, characterised by highly variable, low-to-medium rainfall and lack of irrigation facilities include the states of Andhra Pradesh, Karnataka, Maharashtra, Madhya Pradesh and Gujarat. The Humid tropics with hot and humid summers in Eastern India include the states of Bihar, Jharkhand and Odisha. Data are available for 2005-14 for the SAT region and 2009-10 for the Humid Tropics.

[13] A cultivator household refers to farm households that crop a positive amount of land in a season in a year, where season is defined based on the crop type cultivated by the household and operational holding is the sum of own and net leased/shared land. If a household moves out of the village permanently, it is replaced by a household belonging to the same category.

[14] To elaborate, households are visited every month by the enumerator to collect monthly employment information for individuals listed as household members at the beginning of the agricultural year.

[15] We do not use data from previous survey rounds which began in 2005 because employment data are available at a monthly frequency only from 2010 on-wards for both the regions.

B.1 in the Appendix).[16] The average age of individuals in our sample is a little over 35 years, with almost 7 years of completed education. Approximately 50% of these are women, 65% are married and 40% have a young child under 10 years of age (Panel A, Appendix Table B.1). A household, on average, has 1.56 children and almost two women or men in the 15-65 age group. These households are quite poor with durable asset ownership value of about Rs. 12,000 or USD 165 (Panel B, Appendix Table B.1). We also construct an asset index to capture household wealth through asset ownership in the initial year the household was surveyed.[17]

Table 1 reports the definitions and the summary statistics for the key labor market variables used in the analyses of the individual level monthly employment data. The employment module in the survey records both labor market participation and the number of workdays for each member of the household, by the type of work undertaken - paid farm (as hired labor on another farm), family farm (as labor on farm cultivated by family), family livestock and non-farm. Here, non-farm includes all work in the non-farm sector whether it was done for a wage or in a self-employed activity, with no differentiation between the two in the VDSA data.

Panel A and B of Table 1 show the summary statistics for the variables that capture employment on the extensive margin and on the intensive margin, respectively. Panel A shows that 81% of the sample is engaged in the labor market in a month, on average. There is higher participation in overall farm work (paid farm (15%) and family farm (43%)) relative to non-farm (30%). Conversely, we find higher workdays per month in non-farm (6.55) than farm (paid (2.06) and family (3.47)), as shown in Panel B. This highlights the difference in the intensity of work between the two sectors. Panel C indicates that monthly non-farm real earnings are higher than the monthly earnings of a hired or paid laborer in the farm sector.

[16] Our data set is not balanced since new members join the pool when they cross the threshold of 15 years and there would also be deceased individuals over five years, especially for the elderly population. Even with these constraints, of the individuals observed in 2010, 87% are present in 2011, 85% in 2012, 84% in 2013 and 80% in 2014.

[17] Further details on construction of these variables are mentioned in the note to Table B.1

The overall statistics, however, hide considerable gender differences in labor market participation and outcomes as shown in Appendix Table B.2. The labor force participation rate (LFPR) for women on an average in any given month is 69% while that for men is 92%. Excluding the activity of taking care of family livestock, women's LFPR further falls to 53% while that for men is now 85% in the VDSA data. This figure is quite close to the usual status (worked for at least 30 days in the last year) female LFPR of 46% and male LFPR of 82% obtained using employment data from the nationally representative National Sample Survey (NSS) on employment and unemployment conducted in 2011-12, for the eight states lying in the SAT and Eastern regions of India.[18] Thus, gender disparities in employment in the VDSA data and the nationally representative data for India are comparable for these regions.

This gender gap in employment rates is largely due to the gap in the non-farm sector employment rates of 12% versus 47% for women and men respectively (Panel A, Appendix Table B.2). In terms of employed workdays, women work less than men by almost half, again with considerable heterogeneity across sectors (Panel B, Appendix Table B.2). On average, women spend more days per month in farm work at 4.86 days (paid (2.4) and family (2.46)) than in non-farm work (2.52 days).[19] Further, in both the farm as well as the non-farm sector, real earnings of men are higher than that of women (Panel C, Table B.2). Notably, the gender gap in earnings is much higher in the non-farm sector, with earnings of men eight times that of women. This is partly due to the gender gap in employment and also the gender gap in the daily wage rate.[20] Here, the earnings in the farm sector include wage earnings while the non-farm sector earnings include both wage earnings and profits from self-employed

[18] For an individual to be classified as being in the labor force in the NSS he/she should have engaged in 30 days of work or sought work in a year, as against the VDSA which requires working or seeking work for more than one day in a given month. The VDSA is, thus, likely to give a higher LFPR rate. Also, the NSS surveys, compared to other nationally representative datasets like India Human Development Survey, have been shown to not capture employment in livestock and animal care well which can underestimate women's work, many of whom are involved in this activity. See: IHDS report.

[19] We find a similar pattern of a much larger gender gap in employment in non-farm than the gender gap in farm employment using the 61^{th}, 64^{th}, 66^{th} and 68^{th} rounds of the NSS, as discussed later in Section 4.2.5.

[20] The gender wage gap (ln(male wage)-ln(female wage)) is much higher in the non-farm sector (72%) than in the farm sector (47%).

activities in the sector.

In Section 2 we claimed that women are more likely to work closer to their homes, unlike men. Appendix Table B.2, Panel D, shows data on workplace location by gender. Here, 'Outside village' is defined as an indicator variable that equals one if an individual reports positive employment days outside the village in a given month. Similarly, 'Migration' is an indicator variable that takes a value of one for an individual who reports migrating for work in any activity in a given month. The table shows that 29% of men report working outside the village in any activity in a given month, while only 4% of women do so. Not surprisingly, the gender gap in working as a migrant is 10%. We also calculate the distance to work by measuring the distance from home to the location where the work was undertaken.[21] The unconditional (conditional on paid employment) average distance to work for women is over 77 (269) kms, compared to 2186 (3789) kms in a given month for men.

3.1.2 Rainfall

We use high spatial resolution, daily gridded (0.25 x 0.25 degree) rainfall data collected by the Indian Meteorological Department (IMD) for the last 45 years, i.e., 1971-2015. We match the latitude-longitude of each sampled village to the nearest point on the grid to generate monthly rainfall data at the village level. Following Jayachandran (2006), our measure of the rainfall shock, namely a drought, is defined to occur when the monsoon rainfall lies in the bottom two deciles of the rainfall distribution for that village over the past 45 years. Over 80% of the annual precipitation in India is received during the months of June-September (Turner & Annamalai, 2012) This is the main south-east monsoon season for India and the amount of rainfall received during this period is not only important for the *kharif* season (cropping season during the monsoon) but also in recharging the aquifers which are used

[21] To clarify, this does not reflect the actual distance travelled. For instance, an individual may have stayed in a nearby town for 10 days, which is 100 kms away and the remaining 20 days worked in the village. The total distance to the place of work in that month for that individual will be calculated as $(10 \times 100 + 20 \times 0) = 1000$ kms. If an individual did not engage in any employment in a given month then this measure takes a value of zero.

for irrigation during the *rabi* season (post-monsoon cropping season).[22] Therefore, as in the literature, we define monsoon rainfall as the sum of rainfall in these months for a given agricultural year. Using this definition, Figure 2 shows an upward trend in the number of grids facing droughts between 1901-2017 in India. In our sample, villages received an average monsoon rainfall of 777 mm during 2010-14, 5% lower than the average over the past 45 years (Panel C, Appendix Table B.1). Drought-like conditions were experienced by 26% of the villages during these five years. Following the existing literature, we assign all households within a geographic region, in our case a village, the same value of the drought shock.

We validate our measure of drought by assessing its impact on agricultural output and yield for the sampled villages in the VDSA study in Appendix Table B.3. Here, columns (1) and (2) report the impact of our measure of drought on the log of output and yield for rice, a water-intensive crop mainly cultivated during the *kharif* season, at the village level. As expected, we find a negative effect on the production and yield of rice in the main monsoon cropping season. Rice production falls by 56.1% and yield reduces by 33.2% in a drought year. Additionally, we look at the effect of drought on total farm revenue and profits of a household for a given agricultural season in a year. Appendix Table B.3, column (3) shows that the average farm revenue of a household falls by 28.7%, although imprecise, while profits fall significantly by 50% due to drought (column (4)). These results confirm that our measure of drought accurately captures the shortage of water resulting from low rainfall and thus reducing agricultural productivity.[23]

Additionally, Appendix Table B.4 reports the effect of drought on hours of labor used on the farm as reported in the seasonal input schedule of the survey for each cultivator household in each year. We find a significant reduction in the total labor use on-farm by 25.2% (column (1)). We also look at the effects on labor use by agricultural operations. Since preparation of land is the first operation to be performed at the start of the agriculture season, tasks

[22] We classify months into agricultural seasons for the individual level analyses as follows – *kharif* (June-November), *rabi* (December-March) and *summer* (April-May).

[23] Refer to notes of Appendix Table B.3 on measurement of outcome variables.

included in land preparation are completed even before the onset of the monsoon. Hence, labor use in upstream tasks of preparation of land and sowing is likely to be affected less by a drought shock than downstream labor-intensive tasks like weeding and harvesting.[24] Indeed, we find no significant effect of our measure of drought on labor use in land preparation and sowing (columns (2) and (3)), though the sign is negative and the magnitude is around 4-6%. The requirement for weeding labor falls significantly during a drought by 86.6% (column (4)) as yields plummet and additionally, weed growth gets stunted due to low rainfall. Lastly, column (5) shows that there is a reduction in labor use in the harvesting stage by 53.3%.[25]

3.2 Empirical Strategy

Our main estimating equation is as follows:

$$y^g_{ihvmst} = \beta^g_0 + \beta^g_1 Drought_{vt} + \beta^g_2 X^g_{ihvt} + \delta^g Z^g_{hvt} + \pi^g S_{vt} + D^g_i + D^g_s + D^g_t + \epsilon^g_{ihvmst} \tag{6}$$

where y^g_{ihvmst} represents the labor market outcome for individual i in household h, in village v, in month m in season s and year t. A $Drought$ is an indicator variable that takes a value of one if the monsoon rainfall in the village in year t lies in the first and second decile of the long term rainfall distribution for that village, and zero otherwise. We estimate this equation separately for each gender $g \in \{female, male\}$. Here, β^g_1 estimates the impact of drought on individuals' labor market outcomes, under the identification assumption that the drought shock is uncorrelated with other shocks to labor demand or supply in a village in a given year. Given the unanticipated nature of rainfall and our interest in looking at the reduced form impacts of the drought in equilibrium on labor market outcomes, this assumption holds. Our main coefficient of interest is $\beta^{female}_1 - \beta^{male}_1$, which estimates the impact of drought on women relative to men for a given labor market outcome.

[24] Weeding and harvesting are the most labor intensive operations utilising 107.4 and 219.34 labor hours, respectively, on average in a season in a year.

[25] We find similar results when we consider per-acre labor usage hours as the dependent variable.

In our empirical specification, we transform the continuous dependent variables, i.e. workdays, hours worked, and earnings, using Inverse Hyperbolic Sine (IHS) transformation to take into account zero values for labor use and earnings in a given month for an individual. The advantage of this transformation is that it is defined at zero and the regression coefficients (β_1^g) can be interpreted as a percentage change in the outcome variable due to a drought.[26] On the other hand, for binary outcome variables which capture employment outcomes on the extensive margin, β_1^g is interpreted as percentage point change due to a drought.

X_{ihvt}^g is a vector of individual-level controls that may vary over time, e.g. marital status. Z_{hvt}^g are time-varying household controls that can affect individual employment choices – family composition (number of children, number of female and male members in the working-age group), distance of the house from the nearby market (to capture distance to nearest urban areas where non-farm jobs are available) and average education level (in years) of the household adults. Additionally, the initial asset index and the real value of durables in the first year the household was surveyed is interacted with a linear time trend to take into account differential labor use trends over time by the wealth of the household. We also control for the upper two deciles of monsoon rainfall in a village in a given year (S_{vt}) since a priori it is not clear whether high rainfall reflects a positive or negative productivity shock as higher than usual rainfall can also create a flood-like situation that reduces farm productivity.[27]

We include a range of fixed effects in our specification —D_i^g represents individual fixed effect that controls for unobserved, time-invariant, individual-level factors that may affect labor allocation by men and women in a household, D_s^g represents season fixed effect and D_t^g is an year fixed effect.[28] The standard errors are clustered at the village-season level since

[26]The transformation is given by $log(y) = log(y + (y^2 + 1)^{1/2})$ (Burbidge *et al.* , 1988). We also estimate specifications by taking logs and adding a very small positive value to zero and continue to find similar results. Thus, our results are not sensitive to the IHS transformation in particular.

[27]Existing papers, using district-level data, show that rainfall in the upper deciles can have a positive productivity effect over the entire district (Jayachandran, 2006; Emerick, 2018). In our data we find that the upper deciles of rainfall do not have any positive impact on farm productivity.

[28]We choose to carry out the regression analysis with agricultural season fixed effects even when our data varies at the monthly level. This is to ensure that we accurately capture the seasonal nature of rural labor markets and to keep the analysis consistent with the seasonal agricultural demand. Our results remain unchanged even with month fixed effects.

the drought measure is defined at the village level and shocks within the village for the same season are likely to be correlated.

4 Results

4.1 Main results

We report the estimated effect of drought on labor market outcomes using equation (6) in Table 2. Columns (1)-(2) report the results for overall participation in the labor market, while columns (3)-(4) and columns (5)-(6) report the estimates for its constituents 'Employed' and 'Unemployed', respectively, by gender. Panel A shows the estimates on the extensive margin while Panel B captures the intensive margin impacts as defined earlier in Table 1. In each panel, the first row reports the coefficient on 'Drought'. The second row ('Difference') captures the gender differential between women and men in the effect of drought on the considered outcome. The mean of the binary dependent variable is reported in the last row of Panel A while the mean of the continuous outcome variable (without the IHS transformation) is reported in Panel B.

The results indicate that droughts can have opposing effects on the labor market outcomes of women and men. While the labor force participation of women is affected insignificantly, men increase their participation by 0.6 percentage points (pp) (Panel A, columns (1)-(2)) in response to a drought. Consequently, the gender differential in labor force participation increases by 1.2 pp or 5.2% (at the mean gender difference) when a drought occurs.[29] The overall effect on labor market participation hides another heterogeneity by gender - women are 1.2 pp less likely to be employed (column (3)) but 1.6 pp more likely to seek work (column (5)) when a drought occurs while there is no significant effect on men's employment

[29]The relative effect of drought on LFPR for women versus men in percentage is calculated by dividing the gender differential in employment due to drought, in this case given by 1.2 pp, by the gender differential in mean LFPR rates in the row 'Mean Y' in Panel A of Table 2, given by (92 pp - 69 pp) = 23 pp. This equals 5.2%.

or unemployment. Thus, women are 1.7 pp less likely to be employed and 3.3 pp more likely to look for work, relative to men (row 'Difference'). This implies a fall (rise) in women's employment (unemployment) by 7.1% (82.5%) relative to that of men.

We find similar effects of drought on the intensive margin of labor market outcomes in Panel B of Table 2. While there is a negative but insignificant change in the total days participated in the labor market for both genders (columns (1)-(2)), women's employed workdays fall by 9.9% (column (3)) while the number of days they look for work increases by 7.4% (column (5)). Men's workdays increase insignificantly (column (4)) but their days seeking work reduce by 8% (column (6)). As a result, employed workdays fall significantly more for women by 11%, while there is a significant increase in involuntary unemployment days for women by 15.4%, relative to men.

Next, Table 3 reports the effect of drought on dis-aggregated employment, i.e. by the type of work reported in the corresponding occupational classification for an activity in the data. We use three categories for the type of work – farm (Paid or Family) in columns (1)-(6), livestock (columns (7)-(8)) and non-farm (columns (9)-(10)), as defined in Table 1. Again, Table 3, Panel A shows the estimates on the extensive margin while Panel B reports the intensive margin impacts. Columns (1)-(2), show that there is a negative, though insignificant, effect of drought on total farm employment. However, columns (3)-(6) show that there is heterogeneity across paid and family farm. Women's participation in paid farm work is unaffected (column (3)), but men's falls by 1.5 pp or 12.5% at the mean (column (4)) during a drought. There is no significant effect on participation in family farm for either gender (columns (5)-(6)). Consequently, women's paid farm participation rises by 2.2 pp during drought years, relative to men's. On the other hand, family livestock care work by women falls by 1.7 pp (4% at the mean) in column (7), while men are 2 pp (4.3% of the mean) more likely to participate in the non-farm sector (column (10)). Thus, women's participation in both livestock and non-farm sectors falls by 2 pp and 1.7 pp, respectively, relative to men.

We observe similar effects on the intensive margin in Panel B of Table 3. Women's workdays, relative to men's, on paid farm increase by 6.7% (columns (3)-(4)) but contract in livestock care by 10.8% (columns (7)-(8)) and 10.9% (columns (9)-(10)) in the non-farm sector, respectively. Thus, the overall fall in women's relative employment on both the extensive and intensive margins, reported in Table 2 (columns (3)-(4)), is driven by relatively lower participation by women in livestock and non-farm sectors during a drought. The VDSA data also captures average hours worked per day in the paid farm and the non-farm sectors by an individual in a given month, but not for family farm work. Hence, in our main analyses we look at days worked in a given month as the outcome variable.

However, since the intensity of work within a day can also change during a drought, we examine the effects of a drought on hours worked by those individuals who report working in a sector in a given month. Appendix Table B.5 shows the results for total hours worked in a month as the dependent variable in equation (6) for only paid farm and non-farm work.[30] The overall impact of drought on women's work hours, conditional on working, is negative (column (1)) while there is no effect on men's work hours (column (2)). We also find evidence in support of a reduction in hours worked by women in the paid farm sector by 24.7% due to a drought, conditional on working in the sector in a given month (column (3)). But again, there is no change in the average hours for men (column (4)). Thus, while women continue to work in the farm sector during a drought the intensity of their work declines. On the other hand, a drought does not impact the hours of work in the non-farm sector for either men or women (conditional on working in the sector in a given month).

To summarise, we find a significant gender differential in the responses of women and men to drought in paid farm and non-farm work. Men substitute away from paid farm work (12.5%) and take up non-farm work (4.3%) to cope with the productivity shock due to droughts. The workdays by men in paid farm fall (6.7%) while those in paid non-form work increase (12.4%). In contrast, women are less likely to diversify their workdays away from the

[30]The sample in these regressions is conditional on working in a given month in paid farm or non-farm work (columns (1)-(2)), paid farm work (columns (3)-(4)) and non-farm work (columns (5)-(6)). Hence, there is a reduction in sample size from the earlier individual-level employment regressions in Table 3.

farm to the non-farm sector when a drought occurs. We find a precise zero effect of drought on their paid farm workdays and a positive but imprecise effect on their non-farm workdays, leading to a 10.9% decline in non-farm workdays for women relative to men, during a drought. These findings suggest that the lower returns from farming during drought years push men away from farm work and towards non-farm jobs while women continue to work on the farm with reduced intensity.[31]

Clearly, the above results show that women's participation in the labor market, on the extensive as well as the intensive margin, falls more relative to that of men due to droughts. This raises a natural question as to the impact on their wage earnings. Therefore, we next look at the impact on monthly earnings of women and men and whether there is a gender-differentiated impact on this dimension too due to a negative productivity shock, like drought. In Table 4, columns (1)-(4) report the effect of drought on monthly earnings, columns (5)-(8) on monthly earnings conditional on positive workdays and columns (9)-(13) on daily wage rates (monthly earnings/workdays) for the farm and non-farm sectors and by gender.

The results indicate a negative but insignificant change in the monthly earnings of women in both farm (column (1)) and non-farm (column (3)) work due to a drought. But men's farm earnings fall significantly by 17.2% (column 2) while their non-farm earnings increase by 17.5%. Consequently, although farm earnings fall less for women by 16.8%, their non-farm earnings fall more by 18.2%, relative to that of men. The relative changes in earnings for both the genders are consistent with the results for workdays discussed above. However, summing up the paid farm earnings and non-farm earnings, there is no significant difference in earnings during a drought for either men or women (results omitted for brevity). This shows that men's diversification from the farm to the non-farm sector enables households to cope with a drought shock in terms of recuperating lost earnings from hired work in the farm sector.[32]

[31] Although we do not find any effects of the upper two deciles of rainfall on farm profits and revenue, excess rainfall also leads to an increase in non-farm employment for men relative to women (Emerick, 2018).

[32] It is however important to note that a large part of income loss is due to lower profits on family farm, thus non-farm diversification may not be able to provide full cushioning to the household income losses from

Next, we analyse earnings conditional on working in columns (5)-(8) in Table 4, to gauge how earnings for those who choose to remain in a given type of work change due to droughts. We find that women's earnings fall by 29% (column (5)) while there is an insignificant change for men (column (6)) in event of a drought for paid farm earnings. Conversely, the non-farm conditional earnings are negative but insignificant (9.5%, column (7)) for women and fall significantly for men by 8.3% (column (8)) during a drought. As a result, conditional farm earnings fall more for women by 44.9% relative to men while there is no gender differential in the conditional non-farm earnings.

Lastly, we look at the effects of a drought on the marginal productivity of labor in different types of work. We examine how daily wage rates by gender respond to drought shock in columns (9)-(12), again conditional on working. We find that farm daily wage rates fall more for women (21.3%), compared to men (columns (9)-(10)).[33] On the other hand, non-farm wage rates fall by 6.8% for both women and men but the fall is significant only for men with an insignificant gender differential (columns (11)-(12)). Hence, the results suggest that conditional on working (either on farm or non-farm) women experience a relatively larger fall in farm wage rates – consistent with the existing evidence that wage rate responses to productivity shocks are likely to be larger in the farm sector when labor has fewer options to diversify to the non-farm sector (Jayachandran, 2006).

To sum up, our results show that women's employment suffers relatively more than men's by 11% when a drought strikes. Importantly, the reason being that women continue to work in the farm sector during a drought, albeit with reduced intensity of work, and consequently a lower relative daily wage rate, while men move to non-farm sector employment.

all types of work —own farm, paid farm and livestock. In fact, our findings show that total household incomes (paid farm earnings, livestock earnings, non-farm earnings and profits from farms) fall by around 8% in a drought year.

[33] We also examine the effect of drought on hourly wage rate in the farm sector since we have earlier seen a reduction in hours worked by women in response to drought. We again find that there is a 8.2% decline in hourly wage rates for women in the farm sector in a drought while there is no effect for men.

4.2 Robustness checks

We now check whether the above results are robust to alternate specifications and samples.

4.2.1 Balanced sample

As mentioned previously, our individual-level data set is an unbalanced panel since new household members join and others leave the sample over time. This may bias our estimates above due to sample selection. Therefore, as a robustness check, we restrict the sample to a balanced panel of individuals for whom data are available for all twelve months of each year from 2010-14. This comprises 73% of our original sample. The regression results for labor allocation across sectors remain unchanged and are reported in Panel A of Table 5. We find that women continue to work in the farm sector while men move to the non-farm sector when a drought hits. This leads to an overall greater decline in the days employed for women relative to men by 11.7% (columns (1)-(2)) in a drought year. The previous findings for earnings and wage rates also continue to hold for this sample.

4.2.2 Unconditional sample

Although the VDSA survey records monthly employment information for all household members including migrants, for some individuals the employment information is missing for some months. This can be due to reporting errors or if a member permanently leaves the household for marriage, work or expires. These missing data may not only bias our individual estimates but also the gender differences if either gender is systematically more likely to suffer from misreporting. Therefore, as a robustness check, we consider a full sample of all individuals aged 15 and above who were recorded in the annual household survey at the beginning of the year *unconditional* on being observed in a given month. For the months for which employment data are missing we assign a value of zero to overall workdays and workdays by sector. This increases our original sample by 13%. The regression results are reported in Panel B of Table 5 and remain similar to our main findings above.

4.2.3 Village-specific trends

Throughout our analysis we account for changes in outcome variables over time through year fixed effects. However, our results may be confounded by village specific annual trends in employment and other socio-economic factors. We, therefore, account for village specific linear trends as an additional control in our specification. Our conclusions do not change as shown by the results in Panel C of Table 5.

4.2.4 Alternative measure of drought shock and other controls

We first check if our results on labor market effects of a contemporaneous drought shock are robust to the inclusion of lagged rainfall shock measures. In Appendix Table B.6, columns (1)-(4), we introduce one year lag, in addition to the contemporaneous value, for both our drought and flood shock in the main specification. This allows us to separate the contemporaneous effect of the shock from the lagged effect. Our results remain similar. Second, the literature lacks consensus on a consistent measure of drought. We, therefore, consider two alternative measures of a drought shock. Following the standard agricultural production literature, columns (5)-(8) use a continuous measure of the shock - negative of the standard deviation of monsoon rainfall from its long-run average. Again, we find that men are more likely to move to the farm sector by 6% for every one standard deviation increase in the negative rainfall shock. We find no effect of the drought measure on female farm employment, while that on men is now insignificant. Our second drought measure in columns (9)-(12) uses temperature to capture the negative productivity shock. Thus, a drought is defined as the number of days in the monsoon season that belong to the top 25^{th} percentile of the daily long-run temperature. Our main result of relatively higher take up of non-farm work by men during a drought remains unchanged, though the effect on farm work seems somewhat sensitive to the drought measure captured through temperature, with no significant gender differential for farm work.

4.2.5 Nationally representative data

The VDSA panel data allow us to obtain the most consistent estimates of drought impacts on labor allocation across sectors by accounting for individual-level unobserved heterogeneity. However, the VDSA data are obtained for just 30 villages, which raises concerns about sample selectivity. We, therefore, use the National Sample Survey (NSS), nationally representative data, which provide employment information for a repeated cross-section of households and individuals in each round, to validate our main findings. We use those rounds of data that most closely overlap with our period of analyses above (2005-14) – 2004-05, 2007-08, 2009-10 and 2011-12. We restrict the analyses to rural areas and consider individuals aged 15 years and above. Here farm and non-farm workdays are defined as the sum of the number of days spent in farm and non-farm activities respectively, in the last reference week by an individual.[34] We again take an IHS transformation of workdays to account for zero days of work. Our drought measure is now defined at the district level since this is the smallest administrative unit that can be mapped to an individual in the NSS dataset. The drought indicator takes a value of one when the monsoon rainfall lies in the bottom two deciles of the long-run average for that district and zero otherwise.[35]

The results from this nationwide analysis, reported in the Appendix Table B.7, are consistent with the findings above and show that farm to non-farm diversification in the event of a drought is significant only for men. There is a significant reduction in farm workdays due to a drought for both women (4.9%) and men (3.7%), with no significant gender differential. On the other hand, non-farm workdays increase only for men (3.5%) during a drought. This generates a significant gender differential, whereby women's work in the non-farm sector decreases relative to men's by 3.9% due to a drought. Hence, our main findings from the

[34] 2011-12 is the last available NSS survey round. We do not use the more recent Periodic Labor Force Surveys (PFLS) which replaced the NSS in 2017 as they do not report the operation codes required to create the farm and non-farm work classification. Also, the measurement of hours of work is different across the NSS and the PLFS surveys. The NSS sampling ensures that households are surveyed every quarter in each district to ensure representativeness over the agricultural year.

[35] We construct our measure of district-level rainfall by taking an average of monthly rainfall over the grids of IMD data that overlap with the district, weighted by the area of the overlap with each such grid.

VDSA data continue to hold using an alternative pan-India dataset, not subject to selective sample selection of villages.

5 Mechanism

The above results on the effect of drought on employment as well as wages by gender show that women are less likely to diversify from the farm to the non-farm sector when a negative productivity shock hits the farm sector. Hence, women are more likely to bear the burden of staying in risky employment, which is also less productive and hence pays a lower wage rate, during a drought. What factors explain this gender-differentiated substitution of labor towards non-farm sector employment in response to the climate shock? We take advantage of the rich VDSA data to analyse workplace location and migration decisions by gender, as well as the heterogeneity in our estimates along demographic characteristics that are often determinants of women's mobility.

5.1 Workplace location and seasonal migration

Seasonal migration can be an important coping mechanism during adverse shocks in the agriculture sector. A reduction in farm incomes can also reduce demand for non-farm work within a village. In such a scenario, migration to or travelling to nearby locations may become necessary to find (non-farm) jobs. However, as mentioned previously in Section 3, women are more likely to be restricted in terms of their mobility and may engage in work closer to their homes (Appendix Table B.2, Panel D). Consequently, women may be less likely to explore work opportunities beyond their vicinity even in the event of a negative productivity shock that lowers employment opportunities within the village.

We test this hypothesis by estimating the impact of drought on workplace location and migration (unconditional on employment status) using equation (6). The results are reported in Table 6. In columns (1)-(2), the dependent variable takes a value of one if an individual reports working within the village in a given month in any activity and zero otherwise, while columns (3)-(4) report results when the dependent variable is 'Outside village'. The analysis shows no significant effect of drought on the probability of working within the village for both sexes, though the sign of the coefficient for women is positive. However, in relative terms, women are 1.4 pp or 35% more likely to work within the village in comparison to men (columns (1)-(2)). On the other hand, men are 1.6 pp or 6.4% more likely to work outside the village relative to women when faced with a drought shock (columns (3)-(4)).

In Table 6, columns (5)-(6), we report the results when the dependent variable is an indicator variable for 'Migration' by an individual in a given month, as defined earlier. The probability of migration during a drought increases by 0.8 pp for men (column (6)) or 6.2% of the mean. On the other hand, we find a zero likelihood that women work outside the village (column (3)) or migrate (column (5)) in response to a drought. The reported effects of drought on distance to work for women and men further validate these results.[36] We find an insignificant reduction in distance to work for women (column (7)), while for men the distance to work increases by 19.2% (column (8)) when a drought occurs. Therefore, not only are men more likely to migrate during a drought but they are also likely to travel a longer distance on average in search of work. Women's mobility is, however, constrained.

5.2 Social costs

Do social costs emanating from gender norms influence women's labor mobility and thereby lead to the observed gender-differentiated labor responses? The gendered norms around home production responsibility and sexual 'purity' are likely to reduce women's mobility as observed above and conceptualized in Section 2. Women who have young children and are married are more likely to be responsible for both domestic chores and caregiving duties towards children and elderly, relative to other women. Concerns around sexual purity, besides

[36]Information on distance travelled is available conditional on moving out of the village for work. We give a value of zero to the distance for all people who report working inside the village or who do not work. We then take the IHS transformation of the distance variable to account for zeroes in the dependent variable.

home-production responsibilities, are often higher for adolescent women of marriageable age or married women in the reproductive age, relative to older women.

Table 7, columns (1)-(2) report the heterogeneous effect of drought on non-farm workdays by indicator variables for the young (15-40 year olds), currently married (columns (3)-(4)) and parents with children below the age of 10 years in columns (5)-(6), across gender. Row (A) reports the effect for the base category (i.e., $Z = 0$) while row (B) tests for heterogeneity by the characteristic (Z). The row 'Difference (A)' reports the gender differential between women and men for the base category (i.e., $Z = 0$) while the row named 'Difference ((A)+(B))' does so for the main category (i.e., $Z = 1$). As expected, we find that social constraints translate into significantly lower non-farm days for younger women and women with young children, relative to older women and those without kids, by 8.1% and 13% respectively, when faced with a drought shock (row (B), columns (1) and (5)). We find no significant heterogeneity in female response by marital status.

Our estimates indicate that younger women, married women and those with kids are unable to increase their non-farm days when faced with a drought shock, unlike men who belong to the same groups, as indicated by the significantly negative gender differential for each of these categories (row 'Difference ((A)+(B))'). Although unmarried women and those without young children also work fewer days in the non-farm sector relative to men in the same categories, the negative effect is larger for women having young children. These results highlight the possible role of norms around women's home production responsibilities being higher for those with children and concerns around purity being higher for young women.

We also examine the heterogeneity in the probability of migration due to a drought along these characteristics in Table 8. The coefficients in row 'Difference ((A)+(B))' are all more negative than those in row 'Difference (A)', and statistically significant, showing limited migration by women, relative to men, in these demographic categories during a drought. This reinforces our earlier finding that the prevalence of social norms places a disproportionate burden of home production on women along with concerns around their sexual purity, hindering their mobility and access to alternative sources of work in the event of farm production shocks.

Our proposed mechanism is further validated by the existing evidence that provision of employment close to home helps women cope with negative income shocks disproportionately more than men (Afridi *et al.* , 2021). Indeed, we find that the National Rural Employment Guarantee Scheme (NREGS), a rights-based employment program that provides work within the village and also mandates 30% of rural works for women helps weather the negative labor market effects due to droughts on women. VDSA survey records data on the number of workdays spent by an individual under NREGS each month only for 13 villages out of 30 villages. Appendix Table B.8 shows that NREGS workdays increase insignificantly by 10.5% (column (1)) for women and by 3.2% for men (column (2)) during a drought, rendering the gender difference positive but insignificant. These estimates are imprecise given the data constraints in VDSA for capturing NREGS workdays. Hence, we also use administrative data available from the NREGS public data portal to examine the role of such public works as employment insurance against droughts at the Gram Panchayat (GP) level.[37] Restricting our analysis to the sample of eight states that belong to the VDSA data for the period 2011-14, we find a significant increase in the NREGS person-days for both the sexes as shown in columns (3)-(4) in Appendix Table B.8. While female person-days increase by 37%, the male person-days increase by 33.5%. The gender differential is however significant and women benefit differentially more from this scheme by 3.5%.

There are two alternate explanations of women's limited diversification to the non-farm sector during droughts – lack of non-farm sector skills and safety concerns. We do not find evidence in support of either mechanism. In Table 9 we report the effect of drought on workdays by type of non-farm sector jobs in the VDSA data. We find no gender differential

[37] For administrative purposes, India is divided into 6862 sub-districts. Each sub-district contains about 30 Gram Panchayats (GPs) which are the primary unit of local governance. Each GP comprises approximately 4-5 villages. The data on the annual (April-March) workdays generated for women and men are available at the GP level from NREGA Public Data Portal from 2011 onwards. We construct our measure of drought using rainfall at the centroid of the sub-district. Each GP is then assigned the drought measure of its respective sub-district.

in the skilled non-farm workdays. On the contrary, there is a 6.6% increase in the unskilled non-farm workdays of men relative to women during a drought (columns (1)-(2)). In Appendix Table B.9, we report the heterogeneous effects of a drought on non-farm workdays using NSS data (2004-05, 2007-08, 2009-10 and 2011-12) across high versus low women related crime districts (excluding crimes like domestic violence) classified using National Crime Record Bureau data for 2004. Clearly, the magnitude of the gender difference in the effect of drought on non-farm workdays does not vary across the high and low crime districts. In fact, we find an insignificant gender difference in the effect of drought on non-farm workdays in districts with high incidence of women related crimes (row 'Difference ((A)+(B))').

6 Conclusion

Rural households dependent on the farm sector increasingly face the risk of negative productivity shocks like droughts, especially in rain-fed agriculture systems of developing countries, due to climate change. We find that the impact of climate change may not be gender-neutral, especially in developing countries with social norms that constrain women's labor mobility. Our results show that women not only bear a higher cost of the shock in terms of employment losses but are also unable to cope with these negative effects by diversifying to the less risky, higher return, non-farm work. Women are less likely to migrate and thus are unable to benefit from alternative sources of employment. Thus, as climate shocks become more persistent they can exacerbate existing gender inequities in the labor market and beyond.

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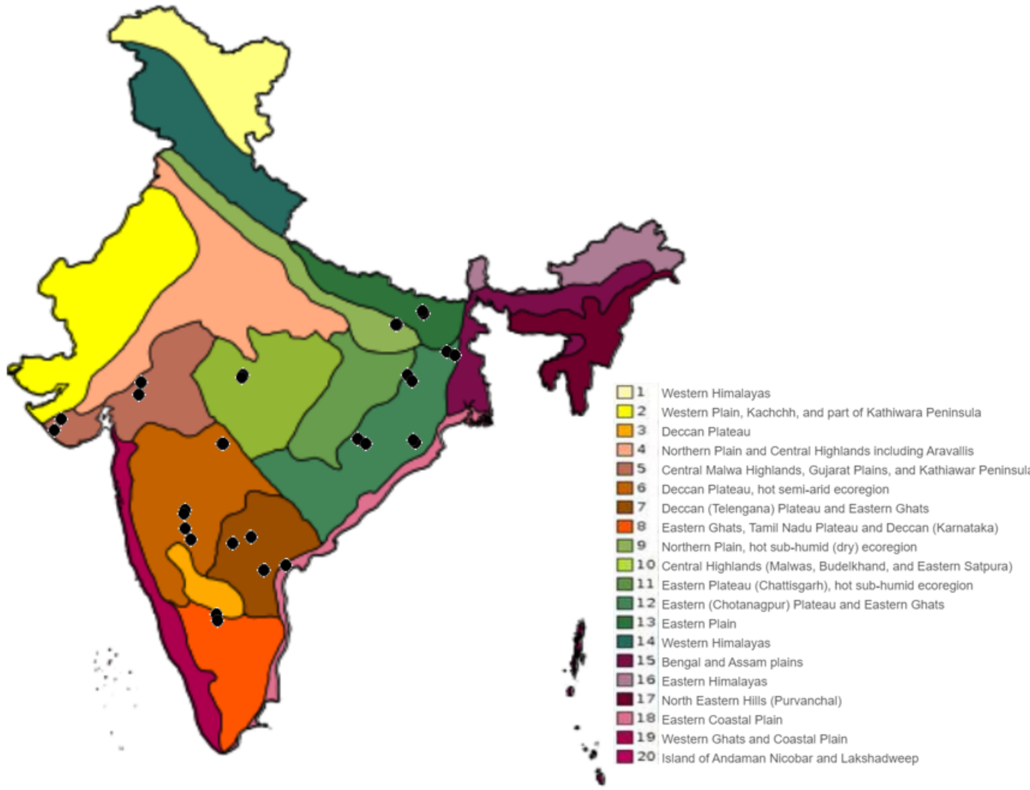
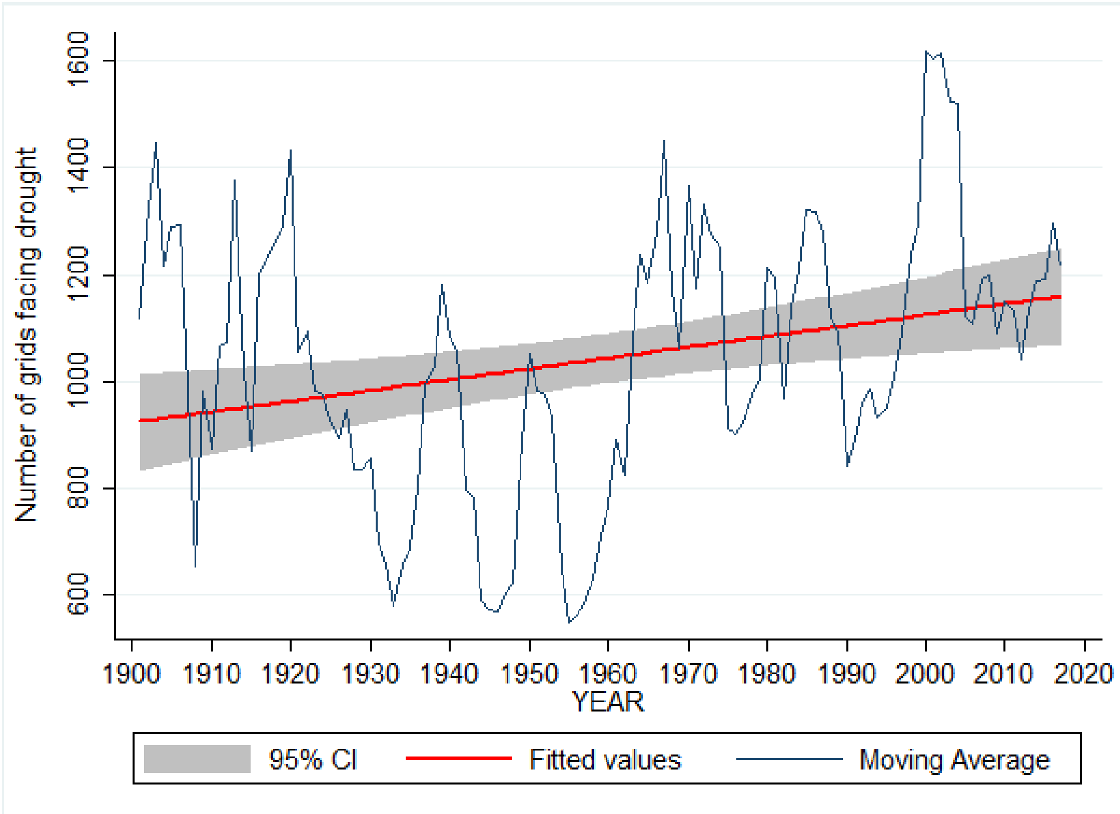
Figure 1: Sampled Villages



Source: VDSA (http://vdsa.icrisat.ac.in/vdsa-map/vdsa-location-map.html).
Note: The black dots mark the 30 villages in the VDSA data. The colors represent different agro-ecological zones as classified by the National Bureau of Soil Survey & Land Use Planning (NBSS & LUP).

Figure 2: Five year moving average of droughts between 1901-2017 across India



Source: IMD data (1901-2017).
Note: A drought is defined to occur when the monsoon rainfall lies in the bottom two deciles of the rainfall distribution for a grid over the past 117 years (1901-2017).

Table 1: Summary Statistics (Individual-month level)

Variable	N	Mean	S.D.	Definition
Panel A: Labor market participation per month (Extensive margin)				
Labor force	278971	0.81	0.39	=1 if employed or sought work, 0 otherwise
Employed	278971	0.81	0.40	=1 if worked for a positive number of days, 0 otherwise
Unemployed	278971	0.08	0.27	=1 if sought work for a positive number of days, 0 otherwise
Paid farm	278971	0.15	0.36	=1 if worked for a positive number of days in paid farm work, 0 otherwise
Family farm	278971	0.43	0.49	=1 if worked for a positive number of days in family farm work, 0 otherwise
Family livestock	278971	0.50	0.49	=1 if worked for a positive number of days on family livestock, 0 otherwise
Non-farm	278971	0.30	0.46	=1 if worked for a positive number of days in non-farm work, 0 otherwise
Panel B: Workdays per month (Intensive margin)				
Labor force days	278971	17.98	14.54	number of days worked or seeking work
Employed days	278971	17.18	14.01	number of days worked (farm plus non-farm)
Unemployed days	278971	0.80	3.61	number of days spent seeking work
Paid farm days	278971	2.06	5.53	number of days worked in paid farm
Family farm days	278971	3.47	5.60	number of days worked in family farm
Family livestock days	278971	5.10	9.27	number of days worked on family livestock
Non-farm days	278971	6.55	10.88	number of days worked in non-farm
Panel C: Real wage earnings per month (Rs.)				
Paid farm earnings	278971	37.75	144.63	real earnings from paid farm work, 0 if unemployed or not working in paid farm
Non-farm earnings	278971	256.68	777.63	real earnings from non-farm work, 0 if unemployed or not working in non-farm
Paid-farm earnings(Conditional)	41401	254.34	293.01	real earnings from farm work if working in paid farm work in that month, missing otherwise
Non-farm earnings(Conditional)	84215	845.28	1221.91	real earnings from non-farm work if working in non-farm work in that month, missing otherwise
Farm wage rate	41401	18.38	12.95	earnings per work day in paid farm in a month
Non-farm wage rate	84215	38.32	69.99	earnings per work day in non-farm in a month

Source: VDSA micro level data.
Note: The sample includes all individuals aged 15 and above in the years 2010-2014. The first column reports the outcome variables used in the analyses for employment and earnings and the last column reports their definitions. Panel A and B show the summary statistics for the full sample for all individuals at a monthly frequency for 2010-2014. In Panel C, the first two rows use the full sample while the following rows show the summary statistics conditional on working in the sector (resulting in the observations being smaller for these rows). Earnings and wage rates are deflated using Consumer Price Index for Agricultural laborers (CPIAL) with the base year 1986-87.

Table 2: Effect of Drought on Labor Market Outcomes

	Labor Force		Employed		Unemployed	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Panel A: Extensive Margin (Participation)						
Drought	-0.006	0.006*	-0.012*	0.004	0.016*	-0.017
	(0.007)	(0.003)	(0.007)	(0.003)	(0.009)	(0.010)
Difference	-0.012*		-0.017***		0.033***	
	(0.006)		(0.006)		(0.010)	
Observations	134,235	144,700	134,235	144,700	134,235	144,700
R-squared	0.654	0.569	0.651	0.560	0.295	0.348
Mean Y	0.69	0.92	0.68	0.92	0.06	0.1
Panel B: Intensive Margin (Workdays)						
Drought	-0.054	-0.005	-0.099**	0.011	0.074*	-0.080*
	(0.056)	(0.037)	(0.049)	(0.038)	(0.043)	(0.048)
Difference	-0.050		-0.110***		0.154***	
	(0.037)		(0.036)		(0.043)	
Observations	134,235	144,700	134,235	144,700	134,235	144,700
R-squared	0.679	0.657	0.674	0.641	0.353	0.381
Individual FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: In Panel A, the dependent variables are indicator variables for the labor force, employed and unemployed status of an individual in a given month in columns (1)-(2), (3)-(4) and (5)-(6), respectively. In the corresponding columns in Panel B, the dependent variables are an IHS transformation of the labor force, employed and unemployed days of an individual in a given month, respectively. Table 1 shows the definition of the variables. In each panel, the first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean Y' denotes the mean value of the dependent variable in Panel A. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 3: Effect of Drought on Employment, by Type of Work

	Farm						Livestock		Non-farm	
	Total		Paid		Family		Family			
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)	Female (9)	Male (10)
Panel A: Extensive Margin (Participation)										
Drought	-0.010	-0.004	0.006	-0.015***	-0.013	-0.003	-0.017*	0.002	0.004	0.020***
	(0.010)	(0.009)	(0.006)	(0.006)	(0.011)	(0.009)	(0.009)	(0.008)	(0.006)	(0.006)
Difference	-0.006		0.022***		-0.010		-0.020**		-0.017**	
	(0.009)		(0.007)		(0.009)		(0.009)		(0.007)	
Observations	134,235	144,700	134,235	144,700	134,235	144,700	134,235	144,700	134,235	144,700
R-squared	0.604	0.583	0.611	0.519	0.597	0.599	0.681	0.670	0.612	0.690
Mean Y	0.45	0.54	0.18	0.12	0.36	0.5	0.42	0.44	0.12	0.47
Panel B: Intensive Margin (Workdays)										
Drought	-0.023	-0.051	-0.000	-0.067*	-0.016	-0.029	-0.136***	-0.028	0.015	0.124***
	(0.055)	(0.048)	(0.031)	(0.035)	(0.048)	(0.044)	(0.046)	(0.041)	(0.041)	(0.037)
Difference	0.028		0.067*		0.013		-0.108**		-0.109***	
	(0.046)		(0.038)		(0.046)		(0.048)		(0.041)	
Observations	134,235	144,700	134,235	144,700	134,235	144,700	134,235	144,700	134,235	144,700
R-squared	0.607	0.616	0.625	0.527	0.590	0.638	0.672	0.691	0.636	0.708
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: In Panel A, the dependent variables in columns (1)-(2), (3)-(4), (5)-(6), (7)-(8) and (9)-(10) are indicator variables for employment in farm, paid farm, family farm, family livestock and non-farm, respectively. In the corresponding columns in Panel B, the dependent variables are an IHS transformation of workdays spent in farm, paid farm, family farm, family livestock and non-farm, respectively. The dependent variable in column (1)-(2) of Panel A ('Total Farm') is an indicator variable that equals one when an individual works either in the paid farm or family farm work in a given month. Similarly, in Panel B it corresponds to an IHS transformation of the sum of workdays spent in paid farm and family farm work. Other dependent variables are defined in Table 1. In each panel, the first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean Y' denotes the mean value of the dependent variable in Panel A. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 4: Effect of Drought on Real Wage Earnings

	Monthly Earnings				Monthly Earnings (Conditional)				Daily Wage Rate			
	Paid Farm		Non-farm		Paid Farm		Non-farm		Paid Farm		Non-farm	
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Drought	-0.003	-0.172**	-0.007	0.175**	-0.290**	0.159	-0.095	-0.083**	-0.075	0.137	-0.068	-0.068**
	(0.058)	(0.066)	(0.073)	(0.076)	(0.127)	(0.151)	(0.098)	(0.040)	(0.062)	(0.096)	(0.053)	(0.029)
Difference	0.168**		-0.182**		-0.449***		-0.012		-0.213**		0.000	
	(0.076)		(0.083)		(0.160)		(0.088)		(0.088)		(0.053)	
Observations	134,235	144,700	134,235	144,700	23,644	17,625	16,614	67,506	23,644	17,625	16,614	67,506
R-squared	0.624	0.523	0.641	0.721	0.493	0.423	0.759	0.711	0.560	0.524	0.791	0.773
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of the monthly earnings from paid activities, monthly earnings (conditional on working) and average daily wage rates of an individual in a given sector of work (paid farm or non-farm) in a given month in columns (1)-(4), (5)-(8) and (9)-(12), respectively. Table 1 shows the definition of the variables. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 5: Effect of Drought on Workdays: Robustness

	Employed		Farm				Livestock		Non-farm	
			Paid		Family		Family			
	Female	Male	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Balanced Sample										
Drought	-0.129**	-0.012	-0.022	-0.075*	-0.006	-0.033	-0.163***	-0.048	0.025	0.107***
	(0.056)	(0.038)	(0.035)	(0.042)	(0.053)	(0.043)	(0.056)	(0.048)	(0.046)	(0.038)
Difference	-0.117***		0.053		0.027		-0.115**		-0.082*	
	(0.041)		(0.044)		(0.048)		(0.054)		(0.045)	
Observations	95,175	107,305	95,175	107,305	95,175	107,305	95,175	107,305	95,175	107,305
Panel B: Unconditional Sample										
Drought	-0.064	0.062	0.013	-0.061*	-0.012	-0.029	-0.111**	-0.011	0.020	0.157***
	(0.051)	(0.056)	(0.030)	(0.033)	(0.042)	(0.041)	(0.048)	(0.039)	(0.034)	(0.043)
Difference	-0.126***		0.074**		0.017		-0.100**		-0.137***	
	(0.044)		(0.034)		(0.040)		(0.050)		(0.047)	
Observations	150,828	164,652	150,828	164,652	150,828	164,652	150,828	164,652	150,828	164,652
Panel C: Village-specific annual trends										
Drought	-0.083*	0.004	-0.014	-0.028	-0.033	-0.018	-0.073*	-0.060*	0.003	0.074**
	(0.045)	(0.027)	(0.029)	(0.029)	(0.045)	(0.043)	(0.037)	(0.031)	(0.035)	(0.032)
Difference	-0.087**		0.014		-0.015		-0.013		-0.070*	
	(0.035)		(0.038)		(0.031)		(0.031)		(0.036)	
Observations	134,235	144,700	134,235	144,700	134,235	144,700	134,235	144,700	134,235	144,700
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of workdays spent in overall employment, paid farm, family farm, livestock and non-farm work by an individual in a given month in columns (1)-(2), (3)-(4), (5)-(6), (7)-(8), and (9)-(10), respectively. Table 1 defines all the outcome variables. Panel A reports the results for the balanced sample of individuals, Panel B reports the results for the sample of all individuals aged 15 and above who were recorded in the annual household survey at the beginning of the year *unconditional* on being observed in a given month and Panel C reports the results with village-specific annual trends. In each panel, the first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Panel C, in addition to the above controls, allows for village-specific annual trends. Standard errors clustered at village-season level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table 6: Effect of Drought on Place of Work

	Within Village		Outside Village		Migration		Distance to Work	
	Female	Male	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Drought	0.006	-0.009	-0.000	0.016***	0.000	0.008**	-0.013	0.192**
	(0.006)	(0.006)	(0.003)	(0.006)	(0.001)	(0.003)	(0.015)	(0.043)
Difference	0.014*		-0.016***		-0.008**		-0.205**	
	(0.007)		(0.006)		(0.003)		(0.070)	
Observations	134,235	144,700	134,235	144,700	134,235	144,700	134,235	144,700
R-squared	0.659	0.603	0.588	0.676	0.643	0.721	0.607	0.701
Mean Y	0.25	0.29	0.04	0.29	0.02	0.13	77.37	2186.09
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables take a value of one for an individual in a given month if the individual spends at least one day engaged in work within the village, work outside the village and work related seasonal migration in that month, in columns (1)-(2), (3)-(4) and (5)-(6), respectively. In columns (7)-(8), the dependent variable is an IHS transformation of the distance (km.) to the workplace for an individual in a given month - defined as the sum of the distance for all work days in a month with zero distance given to work within village and no work. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean Y' denotes the mean value of the dependent variable. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table 7: Heterogeneous Effect of Drought on Non-farm Workdays

Characteristic (Z):	Young		Married		Parent	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Drought	0.063	0.115***	-0.008	0.094	0.049	0.128***
	(0.044)	(0.034)	(0.049)	(0.070)	(0.043)	(0.040)
(B) Z x Drought	-0.081**	0.016	0.030	0.042	-0.130**	-0.018
	(0.039)	(0.053)	(0.045)	(0.071)	(0.050)	(0.062)
Difference (A)	-0.052		-0.103		-0.078	
	[0.2]		[0.09]		[0.06]	
Difference ((A)+(B))	-0.149		-0.115		-0.19	
	[0.01]		[0.02]		[0.02]	
Observations	134,235	144,700	134,235	144,700	134,235	144,700
R-squared	0.636	0.708	0.636	0.708	0.636	0.708
Individual FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variable is an IHS transformation of workdays spent in non-farm work by an individual in a given month. *Young* is an indicator variable for individuals in the 15-40 age category in a given year; *Married* indicates individuals who report marital status as currently married in a given year; *Parent* indicates individuals with children below 10 years of age in a given year. For our main categories ($Z = 1$), these characteristics equal one and zero for the base categories ($Z = 0$). The first row (A) reports the regression coefficients for drought for the base categories while the second row named (B) reports the heterogeneity in the effect by the characteristics. The third row (Difference (A)) reports the gender differential for the base category while the fourth row (Difference (A)+(B)) reports it for the main category. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses and p-values are reported in square brackets (*** p<0.01, ** p<0.05, * p<0.1).

Table 8: Heterogeneous Effect of Drought on Migration

Characteristic (Z):	Young		Married		Parent	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
(A) Drought	-0.001	0.004*	0.001	0.000	0.001	0.004
	(0.001)	(0.003)	(0.002)	(0.007)	(0.001)	(0.004)
(B) Z x Drought	0.002	0.006	-0.001	0.011	-0.002	0.018**
	(0.002)	(0.006)	(0.002)	(0.009)	(0.003)	(0.008)
Difference (A)	-0.004		0.001		-0.003	
	[0.1]		[0.88]		[0.43]	
Difference ((A)+(B))	-0.009		-0.011		-0.023	
	[0.05]		[0]		[0]	
Observations	134,235	144,700	134,235	144,700	134,235	144,700
R-squared	0.644	0.721	0.644	0.721	0.643	0.721
Mean Y (Z=0)	0.01	0.05	0.02	0.17	0.01	0.12
Mean Y (Z=1)	0.02	0.18	0.01	0.11	0.02	0.15
Individual FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variable takes a value of one for an individual who spends one or more days engaged in seasonal migration for work in that month and zero otherwise. *Young* is an indicator variable for individuals in the 15-40 age category in a given year; *Married* indicates individuals who report marital status as currently married in a given year; *Parent* indicates individuals with children below 10 years of age in a given year. For our main categories ($Z = 1$), these characteristics equal one and zero for the base categories ($Z = 0$). The first row (A) reports the regression coefficients for drought for the base categories while the second row named (B) reports the heterogeneity in the effect by the characteristics. The third row (Difference (A)) reports the gender differential for the base category while the fourth row (Difference (A)+(B)) reports it for the main category. 'Mean Y (Z=0)' and 'Mean Y (Z=1)' denote the mean values of the dependent variable for the base and the main category, respectively. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses and p-values are reported in square brackets (*** p<0.01, ** p<0.05, * p<0.1).

Table 9: Effect of Drought on Non-farm Workdays: Skilled vs Unskilled

	Unskilled		Skilled		Business/Salaried	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	-0.001	0.065**	0.021	0.042	-0.024	0.012
	(0.010)	(0.029)	(0.019)	(0.026)	(0.023)	(0.021)
Difference	-0.066**		-0.021		-0.036	
	(0.026)		(0.028)		(0.028)	
Observations	134,235	144,700	134,235	144,700	134,235	144,700
R-squared	0.456	0.586	0.559	0.643	0.659	0.713
Individual FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of workdays spent in different types of non-farm work. Column (1)-(2) report the results for unskilled workdays, column (3)-(4) report the results for skilled workdays and column (5)-(6) report the results for business/salaried workdays. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

ONLINE APPENDIX

A Conceptual Framework (Proof)

The utility maximization exercise in Section 2 gives the following first order conditions for interior solutions:

$$u_a - \Psi = 0 \tag{A.7}$$

$$u_n - p\Psi = 0 \tag{A.8}$$

$$u_{l_a} - \Psi w_a = 0 \tag{A.9}$$

$$u_{l_n} - v_{l_n} - \Psi w_n = 0 \tag{A.10}$$

Total differentiation of equations (A.7) through (A.10) and (2) yields:

$$\begin{pmatrix} u_{11} & u_{12} & u_{13} & u_{13} & -1 \\ u_{12} & u_{22} & u_{23} & u_{23} & -p \\ u_{13} & u_{23} & u_{33} & u_{33} & -w_a \\ u_{13} & u_{23} & u_{33} & u_{33} - v_{11} & -w_n \\ -1 & -p & -w_a & -w_n & 0 \end{pmatrix} \begin{pmatrix} \mathrm{dc}_a \\ \mathrm{dc}_n \\ -\mathrm{dl}_a \\ -\mathrm{dl}_n \\ \mathrm{d}\psi \end{pmatrix} = \begin{pmatrix} 0 \\ \mathrm{dp}\psi \\ \mathrm{dw}_a\psi \\ \mathrm{dw}_n\psi \\ \mathrm{dp}c_n - \mathrm{dw}_a l_a - \mathrm{dw}_n l_n \end{pmatrix} \tag{A.11}$$

Solving the above systems of equations (using Cramer's rule) we obtain the following labor supply responses of women and men to a drought shock (D) for farm (a) and non-farm (n) work:

$$\frac{dl_{af}}{dD} = \left(\frac{dl_{af}}{dw_a}\right) \times \left(\frac{dw_a}{dD}\right) = \left(\frac{R+S}{H+Z}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{A.12}$$

$$\frac{dl_{am}}{dD} = \left(\frac{dl_{am}}{dw_a}\right) \times \left(\frac{dw_a}{dD}\right) = \left(\frac{R}{H}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{A.13}$$

$$\frac{dl_{nf}}{dD} = \left(\frac{dl_{nf}}{dw_a}\right) \times \left(\frac{dw_a}{dD}\right) = \left(\frac{J}{H+Z}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{A.14}$$

$$\frac{dl_{nm}}{dD} = \left(\frac{dl_{nm}}{dw_a}\right) \times \left(\frac{dw_a}{dD}\right) = \left(\frac{J}{H}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{A.15}$$

Under the assumption that a drought is a negative productivity shock in the agricultural sector i.e., $\left(-\frac{dw_a}{dD}\right) > 0$, the sign of the above derivatives i.e., response of the labor supply to drought, will depend on the terms in the first set of parentheses. These terms are a collection of double derivatives and their expressions are given below:

$$\begin{aligned}
J &= w_n(l_1(-u_{11}u_{22}u_{33} + u_{11}{u_{23}}^2 + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22}) \\
&\quad + \psi(-pu_{11}u_{23} + pu_{12}u_{13} + u_{12}u_{23} - u_{13}u_{22})) \\
&\quad + w_a(\psi(-pu_{11}u_{23} + pu_{12}u_{13} + w_n(u_{11}u_{22} - {u_{12}}^2) + u_{12}u_{23} - u_{13}u_{22}) \\
&\quad - l_1(-u_{11}u_{22}u_{33} + u_{11}{u_{23}}^2 + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22})) \\
&\quad + \psi(u_{33}(p^2u_{11} - 2pu_{12} + u_{22}) - (u_{23} - pu_{13})^2) \\
H &= (w_a - w_n)^2(u_{11}({u_{23}}^2 - u_{22}u_{33}) + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22}) \\
Z &= v_{11}(u_{33}(p^2u_{11} - 2pu_{12} + u_{22}) + 2w_a(-pu_{11}u_{23} + pu_{12}u_{13} + u_{12}u_{23} - u_{13}u_{22}) \qquad \text{(A.16)} \\
&\quad - (u_{23} - pu_{13})^2 + w_a^2(u_{11}u_{22} - {u_{12}}^2)) \\
R &= l_1(w_a - w_n)(-u_{11}u_{22}u_{33} + u_{11}{u_{23}}^2 + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22}) \\
&\quad + \psi(-u_{33}(p^2u_{11} - 2pu_{12} + u_{22}) + 2w_n(pu_{11}u_{23} - pu_{12}u_{13} - u_{12}u_{23} + u_{13}u_{22}) \\
&\quad + (u_{23} - pu_{13})^2 + w_n^2({u_{12}}^2 - u_{11}u_{22})) \\
S &= v_{11}(l_1(-pu_{11}u_{23} + pu_{12}u_{13} + w_a(u_{11}u_{22} - {u_{12}}^2) + u_{12}u_{23} - u_{13}u_{22}) \\
&\quad + \psi(p^2u_{11} - 2pu_{12} + u_{22}))
\end{aligned}$$

Using equation (A.15), the conditions under which men diversify to the non-farm sector due to a drought are as follows:

$$\frac{dl_{nm}}{dD} \geq 0 \begin{cases} H > 0 \\ H, J < 0 \end{cases}$$

Using equations (A.14) and (A.15), the conditions for a negative gender differential in non-farm employment due to a drought i.e., women diversify less to the non-farm sector relative to men due to a drought, are given by:

$$\frac{dl_{nf}}{dD} - \frac{dl_{nm}}{dD} \leq 0 \begin{cases} H > 0, 0 \leq Z \\ H < 0, J < 0, |H| < Z or Z < 0 \end{cases}$$

And the converse holds otherwise.

B Additional Tables

Table B.1: Summary Statistics

Variable	Obs	Mean	S.D.	Definition
Panel A: Individual Characteristics				
Age	5931	35.05	17.11	years
Education	5930	7.43	4.94	years of education completed
Female	5931	0.49	0.50	=1 if female, 0 otherwise
Married	5931	0.65	0.48	=1 if currently married, 0 otherwise
Parent	5931	0.25	0.43	=1 if parent of child aged 10 years or below, 0 otherwise
Panel B: Household Characteristics				
Children	1367	1.56	1.52	number of children $<$15 years of age
Working-age women	1367	1.72	0.99	number of women in 15-65 age group
Working-age men	1367	1.88	1.12	number of men in 15-65 age group
Average education	1367	5.25	3.31	mean years of education (members $>$14 years)
Market distance	1367	11.70	7.07	distance from nearest market town (kms.)
Wealth	1367	11641.87	28109.10	value of durable assets (Rs.)
Asset index	1367	-0.20	0.87	PCA of assets
Panel C: Village Characteristics				
Current rainfall	30	776.68	283.32	monsoon rainfall (mm) (2010-14)
Historical rainfall	30	812.64	309.64	monsoon rainfall (mm) (1970-2014)
Drought	30	0.26	0.23	bottom two deciles of the long-run average monsoon rainfall (2010-14)
Flood	30	0.17	0.17	top two deciles of the long-run average monsoon rainfall (2010-14)

Source: VDSA micro level data.
Note: The variables in Panel A and Panel B are at the individual and household level, respectively. The values for wealth and assets index are constructed using data reported by households in the first year it was surveyed. Wealth includes the sum of values of all durable assets owned by the household. The asset index is constructed using the principal components analysis (PCA) on the households' ownership of different assets (bathroom, cooking gas, drinking-water well, electricity, residential house, tap water connection and toilet). Panel C is unique at village level.

Table B.2: Summary Statistics: Individual-month level, by gender

	Female			Male		
Variable	Obs	Mean	S.D.	Obs	Mean	S.D.
Panel A: Labor market participation per month						
Labor force	134259	0.69	0.46	144712	0.92	0.26
Employed	134259	0.68	0.47	144712	0.92	0.27
Unemployed	134259	0.06	0.24	144712	0.10	0.30
Paid farm	134259	0.18	0.38	144712	0.12	0.33
Family farm	134259	0.36	0.48	144712	0.50	0.50
Family livestock	134259	0.42	0.49	144712	0.44	0.50
Non-farm	134259	0.12	0.33	144712	0.47	0.50
Panel B: Workdays per month						
Labor force days	134259	12.86	13.26	144712	22.73	14.06
Employed days	134259	12.28	12.76	144712	21.73	13.57
Unemployed days	134259	0.58	3.11	144712	1.00	4.01
Paid farm days	134259	2.40	5.78	144712	1.74	5.28
Family farm days	134259	2.46	4.42	144712	4.41	6.37
Family livestock days	134259	4.90	9.24	144712	5.28	9.30
Non-farm days	134259	2.52	7.36	144712	10.29	12.21
Unskilled	134259	0.41	3.04	144712	2.54	7.13
Skilled	134259	0.64	3.79	144712	2.83	7.71
Business/Salaried	134259	1.24	5.49	144712	4.68	10.16
Panel C: Real wage earnings per month (Rs.)						
Paid farm earnings	134259	35.02	93.80	144712	40.27	179.30
Non-farm earnings	134259	55.81	265.96	144712	443.04	1013.87
Paid farm earnings (Conditional)	23689	198.50	13.98	17712	329.03	409.44
Non-farm earnings (Conditional)	16661	441.12	612.31	67554	944.95	1310.97
Farm wage rates	23689	14.60	6.52	17712	23.43	17.04
Non-farm wage rates	16661	20.71	23.44	67554	42.66	76.66
Panel D: Workplace in a month						
Within village	134259	0.25	0.43	144712	0.29	0.45
Outside Village	134259	0.04	0.20	144712	0.29	0.46
Migration	134259	0.01	0.11	144712	0.12	0.32
Distance to work (kms.)	134259	77.37	1173.00	144712	2186.09	9264.18
Panel E: Non-farm workdays by demographic groups						
Young	79403	2.60	7.48	85700	12.18	12.48
Older	54856	2.41	7.18	59012	7.55	11.25
Married	102258	2.49	7.23	100815	10.46	12.14
Unmarried	32001	2.63	7.75	43897	9.90	12.36
Parent	36460	2.20	6.73	36267	13.00	12.22
Non-Parent	97799	2.64	7.58	108445	9.39	12.07

Source: VDSA micro level data.
Note: Earnings and wage rates are deflated using the Consumer Price Index for Agricultural laborers (CPIAL) and shows values as of the base year 1986-87 of the index.

Table B.3: Effect of Drought on Farm Output and Productivity

	Rice		All Crops	
	Output	Yield	Revenue	Profit
	(1)	(2)	(3)	(4)
Drought	-0.561**	-0.332*	-0.287	-0.500**
	(0.256)	(0.181)	(0.186)	(0.169)
Observations	114	114	11,606	11,606
R-squared	0.865	0.720	0.384	0.439
Mean	35067.19	4133.66	8404.209	-12540.13
Village FE	✓	✓		
Year FE	✓	✓	✓	✓
Household FE			✓	✓
Season FE			✓	✓
Other controls			✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of the village-level output and yield of rice in columns (1) and (2) and household-level revenue and profit in columns (3) and (4), respectively. The coefficient on *drought* can thus be interpreted as the percentage change in the dependent variable. 'Output' is the total production of rice by all households in a village during the *Kharif* season in a year. 'Yield' is the rice output divided by the total area cultivated under rice in that village in a year. Therefore, columns (1)-(2) are unique at the village-season-year level and restrict to the *Kharif* season only as rice is primarily a *Kharif* crop. 'Revenue' is the total production value of the crops harvested by a cultivating household in a given agricultural season and year. It is obtained by multiplying the price of each crop cultivated by the total production of that crop by the household. 'Profit' is the difference between revenue and cost of inputs including hired labor, but not family labor, in a given agricultural season and year. Both these dependent variables are in real terms (deflated with CPIAL with base as 1986-87) and defined at the household-season-year level. 'Mean' denotes the mean value of the dependent variable (without IHS transformation). The specifications in columns (1) and (2) control for village and year fixed effects while that in columns (3) and (4) controls for household, season, year fixed effects and other controls. Other controls include household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table B.4: Effect of Drought on Hours of Farm Labor Use by Operation

	Total (1)	Preparation (2)	Sowing (3)	Weeding (4)	Harvesting (5)
Drought	-0.252***	-0.063	-0.041	-0.866***	-0.533*
	(0.085)	(0.162)	(0.180)	(0.313)	(0.286)
Observations	8,657	8,657	8,657	8,657	8,657
R-squared	0.570	0.486	0.559	0.520	0.381
Mean	655.1	50.91	26.08	107.4	219.34
Household FE	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of the hours of farm labor usage by a cultivating household in a given season and year. Column (1) reports the effect of drought on total labor use while columns (2)-(5) report it by operation for preparation of land, sowing, weeding and harvesting, respectively. The coefficient on drought can thus be interpreted as the percentage change in the dependent variable. 'Mean' denotes the mean value of the dependent variable (without IHS transformation). All specifications control for household, season, year fixed effects and other controls. Other controls include household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table B.5: Effect of Drought on Hours of Work (Conditional on Working)

	Total		Paid Farm		Non-farm	
	Female	Male	Female	Male	Female	Male
	(1)	(2)	(3)	(4)	(5)	(6)
Drought	-0.111*	0.004	-0.247***	-0.008	-0.032	-0.036
	(0.056)	(0.036)	(0.081)	(0.123)	(0.085)	(0.029)
Difference	-0.115**		-0.239*		0.004	
	(0.047)		(0.122)		(0.074)	
Observations	38,639	83,468	23,644	17,625	16,614	67,506
R-squared	0.495	0.572	0.414	0.532	0.617	0.563
Mean	114.1	162.21	99.69	106.7	123.11	172.52
Individual FE	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of the hours of work spent in total paid activities, paid farm activities and non-farm activities of an individual in a given month in columns (1)-(2), (3)-(4) and (5)-(6), respectively. 'Total' is the sum of the hours spent in paid farm and non-farm work. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean' denotes the mean value of dependent variable (without IHS transformation). All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** p<0.01, ** p<0.05, * p<0.1).

Table B.6: Effect of Drought on Workdays: Robustness (Additional)

	Control: Lagged shocks				Drought Measure 1				Drought Measure 2			
	Paid Farm		Non-farm		Paid Farm		Non-farm		Paid Farm		Non-farm	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)	Female (9)	Male (10)	Female (11)	Male (12)
Drought	-0.007	-0.091**	0.032	0.115**	0.001	0.032	-0.007	0.053*	-0.004*	-0.004	-0.001	0.009***
	(0.034)	(0.039)	(0.050)	(0.044)	(0.022)	(0.023)	(0.021)	(0.030)	(0.002)	(0.003)	(0.003)	(0.004)
Difference	0.084**		-0.083		-0.030		-0.060**		0.000		-0.010***	
	(0.039)		(0.053)		(0.025)		(0.025)		(0.003)		(0.004)	
Observations	134,235	144,700	134,235	144,700	134,235	144,700	134,235	144,700	134,235	144,700	134,235	144,700
R-squared	0.625	0.527	0.636	0.708	0.625	0.527	0.635	0.708	0.625	0.527	0.636	0.708
Individual FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Season FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Year FE	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Other controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Source: VDSA micro level data.
Note: The dependent variables are an IHS transformation of the paid farm and non-farm workdays of an individual in a given month. The specification in columns (1)-(4) is the same as our main specification and additionally controls for a one year lag of drought and flood. In columns (5)-(8), the drought measure ('Measure 1') is the negative of the standard deviation of monsoon rainfall from its long-run average. The drought measure ('Measure 2') in columns (9)-(12) defines drought as the number of days in the monsoon season that fall in the top 25 percentile of the distribution of daily temperatures. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. All specifications control for individual, season, year fixed effects and other controls. Other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table B.7: Effect of Drought on Workdays: Robustness (NSS data)

	Farm		Non-farm	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
Drought	-0.049**	-0.037**	-0.004	0.035**
	(0.019)	(0.018)	(0.010)	(0.015)
Difference	-0.012		-0.039***	
	(0.021)		(0.015)	
Observations	430,905	434,566	430,905	434,566
R-squared	0.190	0.148	0.080	0.151
Mean	1.09	2.46	0.53	2.4
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Other controls	✓	✓	✓	✓

Source: National Sample Survey, Employment and Unemployment rounds (2004-05, 2007-08, 2009-10 and 2011-12).
Note: The sample includes all individuals aged 15 and above in rural regions of India for the NSS rounds between (2005-14), i.e. 2004-05, 2007-08, 2009-10 and 2011-12. The dependent variables are an IHS transformation of the farm and non-farm workdays of an individual in the preceding seven days from the date of the survey in a given year. Here drought is a district level measure. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean' denotes the mean value of workdays in each specification. All specifications control for district and year fixed effects and other controls. Other controls include individual characteristics (age, square of age, education and marital status), household characteristics (religion and social group) and district level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at district level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table B.8: Effect of Drought on NREGS days

	VDSA		NREGS Portal	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
Drought	0.105	0.032	0.370***	0.335***
	(0.094)	(0.171)	(0.074)	(0.073)
Difference	0.073		0.035*	
	(0.156)		(0.019)	
Observations	5,195	5,641	405,105	405,105
R-squared	0.635	0.514	0.700	0.697
Mean	3.6	3.43	2774.52	3394.71
Individual FE	✓	✓		
Year FE	✓	✓	✓	✓
GP FE			✓	✓
Other controls	✓	✓	✓	✓

Source: VDSA micro level data and NREGS Public Data Portal (2011-2014).
Note: The dependent variables are an IHS transformation of the NREGS workdays reported in the VDSA data by an individual in a given year in columns (1) and (2) while in columns (3) and (4) it is the IHS transformation of total NREGS person-days generated in a Gram Panchayat (GP) in a year. The drought measure in columns (1)-(2) is at village level while in columns (3)-(4) is at sub-district level. The first row reports the regression coefficients for drought while the second row ('Difference') reports the difference between the female and male coefficients for drought. 'Mean' denotes the mean value of NREGS days in a given specification (dependent variable without IHS transformation). The specification in columns (1)-(2) control for the individual, year fixed effects and other controls. In these columns, other controls include individual time-varying characteristics (marital status), household time-varying characteristics (number of working-age men and women, number of children, average education level of the household (for members aged 15 and above), distance from the nearest market, the interaction of assets and wealth in the first year of the survey with year fixed effects) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at the village level are reported in parentheses. The specification in columns (3)-(4) control for the GP, year fixed effects. In these columns, other controls include GP level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at sub-district level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Table B.9: Heterogeneous Effect of Drought on Non-farm Workdays: Role of Women's Safety

District characteristic (Z):	Crime Measure 1		Crime Measure 2	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
(A) Drought	-0.015	0.029	-0.017	0.030
	(0.014)	(0.022)	(0.014)	(0.022)
(B) Z x Drought	0.027	0.013	0.030	0.011
	(0.020)	(0.030)	(0.020)	(0.030)
Difference (A)	-0.044		-0.047	
	[0.03]		[0.02]	
Difference ((A)+(B))	-0.029		-0.028	
	[0.18]		[0.2]	
Observations	415,987	419,512	415,987	419,512
R-squared	0.078	0.149	0.078	0.149
Mean (Z=0)	0.47	2.37	0.46	2.36
Mean (Z=1)	0.58	2.42	0.59	2.42
District FE	✓	✓	✓	✓
Year FE	✓	✓	✓	✓
Other controls	✓	✓	✓	✓

Source: NSS (2004-05, 2007-08, 2009-10 and 2011-12) and National Crime Records Bureau (NCRB) (2004).
Note: The dependent variable is an IHS transformation of the non-farm workdays of an individual in the preceding seven days from the date of the survey in a given year. The drought measure is constructed at the district level. Women-related crimes is the total number of crimes (rape, kidnapping and abduction of women, assault on women with intent to outrage her modesty, insult to modesty of women) reported in each district in 2004. 'Crime Measure 1' takes a value of one for districts with above median women-related crimes (per female) and zero otherwise. 'Crime Measure 2' takes a value of one for districts with above median women-related crimes (per person) and zero otherwise. For our main categories ($Z = 1$), these characteristics take a value of one and a value of zero for the base categories ($Z = 0$). The first row (A) reports the regression coefficients for drought for the base category while the second row named (B) reports the heterogeneity by the characteristic. The third row (Difference (A)) reports the gender differential for the base category while the fourth row (Difference (A)+(B)) reports it for the main category. 'Mean (Z=0)' and 'Mean (Z=1)' denote the mean values of the dependent variable (without IHS transformation) for the base and the main category, respectively. The sample includes all individuals aged 15 and above in rural regions of India in the NSS data. Since NCRB data for some districts of NSS are not available in 2004, the number of observations here are lower than the main NSS analysis. All specifications control for district, year fixed effects and other controls. Other controls include individual characteristics (age, square of age, education and marital status), household characteristics (religion and social group) and district level time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at district level are reported in parentheses and p-values are reported in square brackets (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).