The Gendered Effects of Droughts: 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 using unique individual-level panel data for agricultural households in India over half a decade. Accounting for unobserved heterogeneity across individuals, we find that women's workdays are 19% lower than men's when a drought occurs, driven by the 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. We find suggestive evidence in support of social costs emanating from gender norms that constrain women's access to non-farm work opportunities. The results highlight the gendered impact of climate shocks, potentially exacerbating extant gender gaps in the labor market.

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1 Introduction

Climate change has not only resulted in a rise in average temperatures, but it has also increased the incidence and severity of extreme weather events such as droughts and floods (Schiermeier, 2018). Such weather shocks are predicted to rise further if climate change continues unabated (Hsiang & Kopp, 2018; IPCC, 2021). 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. Weather shocks resulting from extreme rainfall are, 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. Additionally, negative short-term productivity shocks such as droughts can potentially exacerbate extant gender differences in labor market outcomes when women's access to off-farm work opportunities is constrained by social factors such as low mobility.

India, with 40% of its workforce employed in the agriculture sector, has experienced an increased incidence, duration and intensity of droughts, over the last century (Figure 1).[1] In this paper, we combine high frequency, individual-level panel data capturing monthly labor supply and seasonal migration during 2010-14 across eight agro-climatic zones of India to analyze the role of labor markets in mitigating the impact of adverse agricultural production shocks due to droughts. Specifically, we examine the short-term impact of deficient rainfall 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 rural areas. In a context where men are often better placed to take advantage of available coping mechanisms through their access to other work via seasonal migration, we assess these labor responses by

[1]See: Indian Meteorological Department (IMD report 2020). A drought is defined to occur for a grid point when rainfall in the main monsoon season (June-September for India) lies in the first two deciles of the long term rainfall distribution of that grid point.

gender. Thus, we also uncover the mechanisms underlying the gender-differentiated impacts on employment.

Our results indicate a fall in women's labor force participation relative to that of men's in the event of a drought. We find that women are 7.1% less likely to be employed but 80% more likely to seek work than men in a drought year. On the intensive margin, women's employment relative to that of men's is lower by 19%. This is because men increase their days spent on non-farm work by 22.5%, but 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 20.1% in drought years. At the same time, women spend 29.4% more days seeking work, relative to men, when faced with a drought shock. Hence, while men diversify to non-farm sector jobs to cope with droughts, women continue to stay in the farm sector, even as they seek work and their real farm wage earnings (conditional on being employed on the farm) and real daily wage rates fall by 38.1% and 11.4%, respectively.

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 1.7 percentage points (pp) and 0.8 pp, respectively, but there is no impact on women's workplace location. Men's higher mobility translates into 18.6% higher non-farm earnings for them relative to women, in the event of a drought.

We find suggestive evidence for social costs emanating from rigid gender norms that place a higher burden of home production and care work on women, as well as concerns around women's sexual 'purity' that inhibit their access to alternative sources of employment beyond their immediate vicinity, as possible explanations behind their lower mobility. Not surprisingly, our analysis shows that women who are younger, married and with young children are not only less likely to divert their labor to the non-farm sector, but are also less likely to migrate relative to men with the same characteristics. 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.

It is well acknowledged that reliance on insurance is mostly absent, while credit markets are incomplete, in agricultural economies (Morduch, 1995). Hence, utilization of labor, specifically a diversification to the non-farm sector, has been documented as a coping strategy adopted by agricultural households during economic shocks that adversely affect crop yields and incomes (Rose, 2001; Minale, 2018; Colmer, 2021; Grabrucker & Grimm, 2021; Blakeslee *et al.* , 2020; Branco & Feres, 2021).[2]

Studies also document a fall in real daily farm wages due to a reduction in demand for labor during a drought, with a larger wage reduction in areas with lower access to non-farm opportunities (Jayachandran, 2006; Mueller & Osgood, 2009; Auffhammer *et al.* , 2012; Mahajan, 2017). Naturally, households often migrate when incomes and livelihoods are adversely affected due to weather shocks like deficient rainfall (see Badiani & Safir (2008); Marchiori *et al.* (2012); Morten (2019), among many others), heat stress (Cai *et al.* , 2016), floods (Giannelli & Canessa, 2022) and storms (Gröger & Zylberberg, 2016).[3]

However, much less is known about the individual, specifically gender-differentiated responses to these shocks. 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 subject to weather shocks. But evidence of gender differences in

[2] Absent this labor reallocation, the economic losses can be enormous – up to 69% higher as estimated by Colmer (2021) 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). See Dell *et al.* (2014) for a review of studies that assess the effects of precipitation and temperature shocks on agricultural yield and productivity as well as adaptation by farmers.

[3] Emerick (2018), using district-level data from India shows that above-normal precipitation increases the share of non-farm sector employment. This is driven by increased local demand for goods that attract labor to the non-farm sector. Thus, when estimating the effects of negative precipitation shocks on employment outcomes, we control for positive precipitation shocks to allow for differential changes in sectoral employment in periods of both low productivity shocks (due to distress) and high productivity shocks (due to increased local demand).

labor response for smoothing the risk emanating from weather shocks, is almost absent, with a few exceptions. Huang *et al.* (2020) use retrospective employment data for three years from rural China to examine labor re-allocation, in response to temperature and precipitation change, from farm to non-farm activities by gender at the province level. They find no differential impact in take up of non-farm work by gender due to such shocks. 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 while men allocate more time to off-farm labor employment during a drought. However, none of these papers addresses either individual or household level unobserved heterogeneity in assessing the response to climate shocks or explore the underlying mechanisms.[4]

While the existing literature largely 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 agricultural productivity shock. Second, and relatedly, unlike the aggregate geographical data used in most previous studies, we underline the potential gender-differentiated impact of climatic shocks such as droughts utilizing novel individual-level panel data over eight agro-climatic zones, collected at a monthly frequency. We are thus able to account for seasonal impacts that are relevant to the agricultural sector.

Furthermore, none of the existing studies provide mechanisms behind the observed gender-differentiated impacts. 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

[4] In the Indian context, Maitra & Tagat (2019) examine the gender-differential in the labor responses to rainfall shocks for self-employed and wage work at the district level, but not substitution towards the non-farm sector. They find that men increase their regular wage work in response to negative rainfall shocks while there is no change for women. 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. Neither delves into the mechanisms that cause this gendered response, in general, or the location of non-farm work, specifically.

allow us to investigate coping mechanisms from farm income losses through engagement in seasonal migration, and the extent to which men and women are able to access non-farm sources of employment through this channel. Our research, thus, also speaks to the literature on migration, by highlighting the role of seasonal migration as a coping mechanism and its potential in exacerbating the impact of weather shocks on gender equality (Cattaneo *et al.* , 2019).[5]

Lastly, through our heterogeneity analyses of the individual-level data which exploits the age, marital status, and parenthood of an individual, we are able to show that social norms around the gendered nature of household production and women's purity place a cost on women's access to employment opportunities outside their village.

Indeed, we find suggestive evidence that public employment programs that provide work close to women's homes, not only mitigate production risks in agriculture in the short-run but also stem gender disparities in employment opportunities. Social norms, thus, can plausibly explain the observed gender-differentiated impacts of droughts in our context. This mechanism, to the best of our knowledge, has not been previously highlighted in the literature. While we do not find evidence in support of gender skill differentials or safety concerns, we are unable to test for gender-differentiated changes in demand for labor in the farm and non-farm sectors, due to data constraints.

The above findings are in contrast to the theoretical prediction and empirical evidence which shows 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). Our findings show that while women are more likely to seek work due to negative aggregate income shocks, their employment may not increase if

[5]There is, however, no consensus in this literature since the search for alternative locations for residence can increase while credit constraints can decrease permanent migration. Dillon *et al.* (2011) and Gray & Mueller (2012) find that men are more likely to permanently migrate in response to temperature increases in Nigeria and droughts in Ethiopia. On the other hand, Baez *et al.* (2017) find increased permanent migration by women in response to heat exposure in the Latin America and Caribbean region. The responses can also vary by the nature of the negative productivity shock such as harvest losses vs earthquakes (Halliday, 2012). Importantly, while the existing literature has largely focused on permanent migration, our main interest in this paper is to look at the channel of seasonal migration for alternative employment in the face of shock.

their labor mobility is limited. Additionally, climatic shocks may have long-term effects. Our cross-sectional estimates indicate that gender gaps in non-farm employment and migration are larger in villages facing higher risks from rainfall variability, suggesting that men may permanently shift their occupational structure to the less risky non-farm sector. Indeed, Albert *et al.* (2021) finds that regions facing increased frequency of droughts witness a shift in employment towards the non-farm sector and an increase in population outflows over two decades in Brazil. In contrast, Liu *et al.* (2021) and Jessoe *et al.* (2018) show that long-term temperature increases reduce non-farm employment share and lower rural-urban migration rates in India and Mexico, respectively. Our findings, thus, call for further research on the longer-term effects of weather shocks, from a gender perspective.

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. We 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.

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 75 km while it is 3832 km for non-farm work (conditional on non-farm employment). This indicates the important role played by seasonal migration for access to non-farm jobs. Even if we exclude migration, a large gap persists in the average distance to farm work (4 km) and non-farm work (212 km).

Thus, social costs can arise due to the stigma associated with women's participation in work that reduces their time at home (due to increased travel times) – 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; Heath & Mobarak, 2015; Andrabi *et al.* , 2013).[6] 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). This can lead to higher social costs for non-farm work for women because such work is predominantly male-dominated in India, a feature of the Indian labor market we discuss later.

The utility maximization problem for an agent, is thus, 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

[6]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 the 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.[7]

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

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

where θ is the productivity parameter, B denotes the land used in production, L_a is total labor employed on the farm and ϵ is the share parameter.[8]

A negative productivity shock to the farm sector denoted by D, specifically drought, reduces θ. Consequently, this reduces the profit maximising equilibrium labor demand ($\frac{dL_a}{dD} < 0$) and depresses wage rates ($\frac{dw_a}{dD} < 0$). The detailed proofs are presented in Appendix A. We further assume that production in the non-farm sector is independent of negative agricultural productivity shocks such as a drought.[9]

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

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

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

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

[8]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.

[9]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 weather shocks affect the farm sector more (Pachauri *et al.* , 2014), our theoretical predictions go through.

The terms H, R, S, J and Z, defined in Appendix A, are a collection of double derivatives of the utility function. 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, it can be shown that $R<0$ 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 or when male dominated 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 our analysis.

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.[10] 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.[11] Figure B.1 in the Appendix 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 of this year 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.[12] Detailed information on sampled households' socio-economic characteristics, agricultural production and livelihoods are collected annually, at the beginning of each agricultural year in July.

The survey records employment-related details for every month of each year for each member of a sampled household, including temporary migrants.[13] We use data on all individuals aged 15 and above in the five latest rounds of the survey from 2010-2014.[14] We,

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

[11] 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 2009-14 for the Humid Tropics.

[12] A cultivator household refers to farm households that crop a positive amount of land in a season in a year, where season is defined on the basis of 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.

[13] 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.

[14] We do not use data from previous survey rounds which began in 2005 because employment data are

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 279,935 individual-month year observations (see Table B.1 in the Appendix).[15] The average age of individuals in our sample is a little over 35 years, with over 7 years of completed education. Approximately 50% of these are women, 65% are married and 25% have a young child below the age of 10 years (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 a 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.[16]

Table B.2 in the Appendix 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 others 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 B.2 in the Appendix show the summary statistics for the variables that capture employment on the extensive margin and on the intensive margin, respectively. Panel A shows that on average 81% of the sample is engaged in the labor market in a month. There is higher participation in overall farm work (paid farm (15%) and family farm (43%)) relative to non-farm work (30%). Conversely, we find higher workdays per month in non-farm

available at a monthly frequency only from 2010 on-wards for both the regions.

[15] 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 a span of five years, especially for the elderly population. Even with these constraints, of the individuals observed in 2010, 93% are present in 2011, 89% in 2012, 87% in 2013, and 82% in 2014.

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

(6.53) than farm (paid (2.05) and family (3.46)), 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.

These overall statistics, however, hide considerable gender differences in labor market participation and outcomes as shown in Table 1. 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 becomes 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.[17] 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 difference in the non-farm sector employment rates of 12% and 47% for women and men respectively (Panel A, Table 1). In terms of employed workdays, women work less than men by almost half, again with considerable heterogeneity across sectors (Panel B, Table 1). On average, women spend more days per month in farm work at 4.84 days (paid (2.39) and family (2.45)) than in non-farm work (2.51 days).[18] 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 1). 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

[17] 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.

[18] 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.

rate.[19] 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 activities in the sector.

In Section 2 we claimed that women are more likely to work closer to their homes, unlike men. Table 1, 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 11%. We also calculate the distance to work by measuring the distance from home to the location where the work was undertaken.[20] The unconditional (conditional on paid employment) average distance to work, including seasonal migration for work, is over 77 (268) km for women, compared to 2179 (3776) km for men in a given month.

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

[19] The gender wage gap (ln(male wage)-ln(female wage)) is much higher in the non-farm sector (72%) than in the farm sector (41%).

[20] 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 km away, and in 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 $(10\times100 + 20\times0)=1000$ km. If an individual did not engage in any employment in a given month then this measure takes a value of zero.

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 for irrigation during the *rabi* season (post-monsoon cropping season).[21] Therefore, as in the literature, we define monsoon rainfall in a given agricultural year as the sum of rainfall during June-September.[22] Using this definition, Figure 1 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. The detailed estimation strategy and results are discussed in Appendix B. As expected, we find a negative effect on the production and yield of rice by 56.1% and 33.2% respectively, in a drought year. We also find that the average farm revenue of a household falls by 27.7%, although imprecisely, while profits fall significantly by 49.5% due to drought. These results reported in Appendix Table B.3 confirm that our measure of drought accurately captures the shortage of water resulting from low rainfall, thus reducing agricultural productivity.[23] Lastly, we find a significant reduction in the total labor use on the farm by 24% (Appendix Table B.4), with labor use in upstream tasks of preparation of land and sowing affected less than downstream labor-intensive tasks like weeding and harvesting by a drought shock.[24] Labor used for weeding falls by 84.2%, as weed growth gets stunted due to low rainfall and that for harvesting falls by 50.3%.[25]

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

[22]For instance, to define the drought shock for the agricultural year 2010-11, we sum up the village level rainfall for the monsoon months of June 2010-September 2011 and obtain the drought measure using the aforementioned methodology. We then assign this drought shock to the months July 2010 onwards until the onset of the next monsoon in 2011, for all households in that village.

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

[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.

3.2 Empirical Strategy

Our main estimating equation is as follows:

$$y^g_{ihvmst} = \beta^g_0 + \beta^g_1 Drought_{vt} + \beta^g_2 X_{ihvt} + \delta^g Z_{hvt} + \pi^g S_{vt} + D^g_i + D^g_s + D^g_t + \epsilon^g_{ihvmst} \quad (6)$$

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 v in year t lies in the first or 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.

In our empirical specification, we transform the continuous dependent variables, i.e., workdays and earnings, using the 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^g_1) 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^g_1 is interpreted as percentage point change due to a drought.

[26] The transformation is given by $log(y) = log(y + (y^2 + 1)^{1/2})$ (Burbidge *et al.* , 1988). While this transformation estimates the effect in percent terms with little error for variables with values greater than 10, it underestimates the effect if the variable takes values below 10 (Bellemare & Wichman, 2020). Since the average workdays in our sample are below this threshold, we multiply them by 10 to reduce the error. We also estimate specifications by taking logs and adding a very small positive value to zero and continue to find similar results in percentage terms. Thus, our results are not sensitive to the IHS transformation in particular.

X_{ihvt} is a vector of individual-level controls that may vary over time, e.g. marital status. Z_{hvt} 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), the 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, we interact the initial asset index and the real value of durables in the first year the household was surveyed 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 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,

[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 village-level 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.

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 in Table B.2. 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 outcome variables.[29] The mean of the binary dependent variable is reported in the last row of Panel A.

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.[30] 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 or unemployment. Thus, women are 1.7 pp less likely to be employed and 3.2 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% (80%) 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. There is a negative but insignificant change in the total days participated in the labor market for women (column (1)). Women's employed workdays fall by 15.3% (column (3)) while the number of days they look for work increase by 14.4% (column (5)). Men's total workdays in labor market, as well as employed workdays, increase insignificantly

[29]We run a fully interacted specification using the pooled sample of men and women to estimate the coefficients and standard errors for this difference. To elaborate, we interact the drought measure, as well as all other controls, with a female dummy variable that equals one for women and zero for men.

[30]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%.

(column (2) and (4)) but their days seeking work reduce by 15% (column (6)). As a result, employed workdays fall significantly more for women by 19%, while there is a significant increase in involuntary unemployment days for women by 29.4%, relative to men.

Next, Table 3 reports the effect of drought on dis-aggregated employment, i.e., by the nature of engagement in different types of work. 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 B.2. Again, Table 3, Panel A shows the estimates on the extensive margin while Panel B reports it for the intensive margin. 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 1.6 pp or 13.3% 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 2.1 pp during drought years, relative to men's. On the other hand, family livestock care work by women falls by 1.6 pp (3.8% at the mean) in column (7), while men are 2.1 pp (4.5% of the mean) more likely to participate in non-farm sector work (column (10)). Thus, women's participation in both livestock and non-farm sectors falls by 1.9 pp and 1.8 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 15.3% (columns (3)-(4)) but contract in livestock care by 18.9% (columns (7)-(8)) and 20.1% (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 non-farm sectors by an individual in a given month, but not for family farm and family livestock work. In Appendix B, we examine the effect of drought on total hours worked in paid farm and non-farm work categories. We find that women's hours, relative to men's, in paid farm increase by 13.1% but contract in the non-farm sector by 18.7% (Appendix Table B.5). Thus, our previous findings for monthly workdays continue to hold for monthly hours of work as well.

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 (13.3%) and take up non-farm work (4.5%) to cope with the productivity shock due to droughts. The workdays by men in paid farm fall (13.7%) while those in paid non-farm work increase (22.5%). In contrast, women are less likely to diversify their workdays away from the farm to the non-farm sector when a drought occurs. We find a decline in women's livestock workdays by 21% but no effect on women's farm and non-farm workdays. The gendered effects lead to a 15.3% gain in farm workdays while the non-farm and livestock workdays decline by 20.1% and 18.9%, respectively, for women relative to men, during a drought.[31] 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.[32]

Clearly, the above results show that women's employment, on the extensive as well as the intensive margin, falls more relative to that of men due to droughts. 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)-(12) on daily wage rates (monthly earnings/workdays) for the farm and non-farm sectors and by gender.

The results indicate an 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 18.5% (column 2) while their non-farm earnings increase by 17.5%. Consequently, although farm earnings fall less for women by 18.9%, their non-farm

[31]We also check for multiple hypothesis testing using the standard FDR Q method given the multiple outcomes in our analysis (Anderson, 2008; Benjamini & Yekutieli, 2001). Our main result of diversification to non-farm work by men on extensive as well as intensive margins during a drought continues to remain significant.

[32]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).

earnings fall more by 18.6%, relative to that of men. The relative changes in earnings for both 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.[33]

Next, we analyse earnings conditional on working in columns (5)-(8) in Table 4, to gauge how earnings for those who choose to be engaged in a given type of work change due to droughts. We find that women's earnings fall by 38.1% (column (5)) while there is an insignificant change for men (column (6)) in the event of a drought for paid farm earnings.[34] Conversely, the non-farm conditional earnings are negative but insignificant (10%, column (7)) for women and fall significantly for men by 9% (column (8)) during a drought. As a result, conditional farm earnings fall more for women by 34.7% relative to men while there is no gender differential in the conditional non-farm earnings.

Lastly, we look at the effects of 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 (11.4%) while there is no significant effect for men (columns (9)-(10)).[35] On the other hand, non-farm wage rates fall by 7-8% 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 women experience a relatively larger

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

[34]The negative effect of droughts on conditional paid farm earnings of women with an insignificant effect on their overall monthly paid farm earnings can be explained by women's higher participation and increased workdays, albeit insignificant, in the farm sector (Table 3, column (3)).

[35]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 9.4% decline in hourly wage rates for women in the farm sector in a drought while there is no effect for men.

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 days in employment fall relative to men's by 19% when a drought strikes. This is due to no change in their total days of work in the farm or the non-farm sectors, albeit a fall in their workdays in the livestock sector. However, men's days of work in the non-farm sector increase during a drought. Thus, women continue to work in the farm sector during a drought, but with reduced intensity of work, and consequently a lower relative daily wage rate, while men move to non-farm sector employment. In congruence with our main results, we not only find that men residing in villages with higher rainfall variance allocate more workdays to the non-farm sector, but also observe a larger gender gap in non-farm sector employment in these areas.[36] Thus, both the short-term and possibly the longer-term effects of climate change can be deleterious for women in terms of exacerbating gender gaps in non-farm employment.

4.2 Robustness checks

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 73.7% 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

[36] Here, rainfall variance is measured by the observed variability in monsoon rainfall. A village is classified as high variability when its coefficient of variation of monsoon rainfall (=Standard Deviation/Mean) is above the median of the distribution across villages.

women relative to men by 19.6% (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 4.2%. 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 and temperature. In Appendix Table B.6, columns (1)-(4), we introduce one year lag, in addition to the contemporaneous value, for both our drought and excess rainfall shock in the main specification. This allows us to separate the contemporaneous effect of the shock from the lagged effect. Our results for the contemporaneous drought shock remain similar. In columns (5)-(8), we introduce controls for temperature and its square to check if the drought effects remain significant even after controlling for temperature fluctuations.[37] We measure temperature as the Harmful Degree Days (HDDs) during the monsoon season defined as the sum of the deviations of daily maximum temperature above the median of its long-run village-level monthly maximum temperature over the monsoon period. Our findings on the effects of drought on paid farm and non-farm work remain unchanged.

Second, the literature lacks consensus on a consistent measure of drought. We, therefore, consider two alternative measures of a drought shock in Appendix Table B.7. Following the standard agricultural production literature, columns (1)-(4) 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 non-farm sector by 10% for every one standard deviation increase in the negative rainfall shock. We find no significant effect of the drought measure on female or male paid farm employment. Our second drought measure in columns (5)-(8) uses temperature to capture the negative productivity shock. It defines drought as the Harmful Degree Days (HDDs) of temperature over the monsoon season (without controlling for drought resulting from low precipitation). Our results using this alternative definition of drought remain similar, with an additional HDD reducing the paid farm workdays and increasing non-farm workdays of men equally by 0.3%. We find no significant effect for women either for the farm or non-farm work. Consequently, paid farm (non-farm) workdays increase (fall) more for women by 0.3%, relative to men for an additional HDD.

[37] While, temperature and drought shock may be correlated (0.29, $p<0.01$), the variation in temperature over half a decade is not large for our time period of study.

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 collected for just 30 villages, which raises concerns about sample selectivity. We, therefore, use the National Sample Survey (NSS), nationally representative data, which provides employment information for a repeated cross-section of households and individuals in each round, to validate our main findings. We use recent rounds of data that most closely overlap with our period of analyses above – 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.[38] We again take an IHS transformation of workdays to account for zero days of work.[39] 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 in a given year and zero otherwise.[40]

The results from this nationwide analysis, reported in the Appendix Table B.8, are consistent with the findings using the VDSA data 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 drought for both women (12.1%) and men (8.3%), with no significant gender differential. On the other hand, non-farm workdays increase only for men (9.7%) during a drought. This generates a significant gender differential, whereby women's work in

[38] 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.

[39] Before undertaking this transformation, we multiply them by 10 to reduce the error as discussed in Section 3.2.

[40] 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.

the non-farm sector decreases relative to men's by 10% due to a drought. Hence, our main findings from the VDSA data continue to hold using an alternative pan-India dataset.

5 Mechanisms

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 weather 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 by 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 1, 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 during a drought (columns (1)-(2)). On the other hand, men are 1.8 pp or 7.2% 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 drought. The reported effects of drought on the distance to work for women and men further validate these results.[41] We find an insignificant change in distance to work for women (column (7)), while for men the distance to work increases by 19.9% (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.[42]

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

[41]Information on distance travelled is available conditional on moving out of the village for work. We assign a value of zero to the distance travelled for those 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.

[42]We also find that male migration for work is relatively higher than that of females in villages that experience greater variability in monsoon rainfall, suggesting a longer-term impact on the structure of the labor market due to extreme weather events.

married are more likely to be responsible for both domestic chores and care-giving duties towards children and elderly, relative to other women. Concerns around sexual purity, besides 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 (15-39 year olds), currently married (columns (3)-(4)) and parents to 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 14.6% and 21.4% 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 significant 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 married women and 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.* , 2022). 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 33% 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.9 shows that NREGS workdays increase insignificantly by 12.7% (column (1)) for women and by 1.1% 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.[43] Restricting our analysis to the sample of eight states of the VDSA data for the period 2011-14, we find that women benefit differentially more from this scheme by 3.5% (Appendix Table B.9).

There are two alternative 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

[43]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 10.6% increase in the unskilled non-farm workdays of men relative to women during a drought (columns (1)-(2)). In Appendix Table B.10, 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 Records 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 a significant gender difference in the effect of drought on non-farm workdays in both types of districts (row 'Difference ((A)+(B))').

It is theoretically possible that our findings can be explained by differential changes in demand in the farm/non-farm sector across gender when droughts occur. However, this is difficult to test since we observe only equilibrium employment outcomes. Additionally, it is less likely that demand would vary differentially by age, marital status and parenthood, between women and men.[44] Overall, the above findings provide plausible evidence that social norms around home production and sexual purity restrict female mobility, thus constraining their ability to diversify to the non-farm sector when negative productivity shocks occur in the farm sector.

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 extreme weather events resulting from adverse climatic changes may not be gender-neutral, especially in developing countries with social norms that constrain women's labor mobility. Our results show that women are more likely to face employment losses as they are unable to cope with these negative effects

[44] Lower bargaining power of women within the household can also constrain their mobility and hence access to non-farm work outside the village. To the extent that social norms determine the relative bargaining power of spouses within a household (Jayachandran, 2015), our findings can be explained by these norms.

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. While the observed choices may be optimal for households, our results show that as climate shocks become more persistent they can exacerbate existing gender inequities in the labor market and beyond. Thus, gender-neutral shocks can have gendered impacts.

References

Afridi, Farzana, Bishnu, Monisankar, & Mahajan, Kanika. 2019. What Determines Women's Labor Supply? The Role of Home Productivity and Social Norms. *IZA Discussion Paper No. 12666.*

Afridi, Farzana, Mahajan, Kanika, & Sangwan, Nikita. 2022. Employment guaranteed? social protection during a pandemic. *Oxford Open Economics*, **1**.

Agamile, Peter, Dimova, Ralitza, & Golan, Jennifer. 2021. Crop Choice, Drought and Gender: New Insights from Smallholdersâ Response to Weather Shocks in Rural Uganda. *Journal of Agricultural Economics*, **72**(3), 829–856.

Albert, Christoph, Bustos, Paula, & Ponticelli, Jacopo. 2021. *The Effects of Climate Change on Labor and Capital Reallocation.* Tech. rept. National Bureau of Economic Research.

Anderson, Michael L. 2008. Multiple inference and gender differences in the effects of early intervention: A reevaluation of the Abecedarian, Perry Preschool, and Early Training Projects. *Journal of the American statistical Association*, **103**(484), 1481–1495.

Andrabi, Tahir, Das, Jishnu, & Khwaja, Asim Ijaz. 2013. Students today, teachers tomorrow: Identifying constraints on the provision of education. *Journal of Public Economics*, **100**, 1–14.

Attanasio, Orazio, Low, Hamish, & Sánchez-Marcos, Virginia. 2005. Female labor supply as insurance against idiosyncratic risk. *Journal of the European Economic Association*, **3**(2-3), 755–764.

Auffhammer, Maximilian, Ramanathan, Veerabhadran, & Vincent, Jeffrey R. 2012. Climate change, the monsoon, and rice yield in India. *Climatic Change*, **111**(2), 411–424.

Badiani, Reena, & Safir, Abla. 2008. Coping with aggregate shocks: Temporary migration and other labor responses to climatic shocks in rural India. *Presentation to the European Society for Population Economics, Seville, June*, 11–13.

Baez, Javier, Caruso, German, Mueller, Valerie, & Niu, Chiyu. 2017. Heat exposure and youth migration in Central America and the Caribbean. *American Economic Review*, **107**(5), 446–50.

Bellemare, Marc F, & Wichman, Casey J. 2020. Elasticities and the inverse hyperbolic sine transformation. *Oxford Bulletin of Economics and Statistics*, **82**(1), 50–61.

Benjamini, Yoav, & Yekutieli, Daniel. 2001. The control of the false discovery rate in multiple testing under dependency. *Annals of statistics*, 1165–1188.

Blakeslee, David, Fishman, Ram, & Srinivasan, Veena. 2020. Way down in the hole: Adaptation to long-term water loss in rural India. *American Economic Review*, **110**(1), 200–224.

Branco, Danyelle, & Feres, Jose. 2021. Weather Shocks and Labor Allocation: Evidence from Rural Brazil. *American Journal of Agricultural Economics*, **103**(4), 1359–1377.

Burbidge, John B, Magee, Lonnie, & Robb, A Leslie. 1988. Alternative transformations to handle extreme values of the dependent variable. *Journal of the American Statistical Association*, **83**(401), 123–127.

Cai, Ruohong, Feng, Shuaizhang, Oppenheimer, Michael, & Pytlikova, Mariola. 2016. Climate variability and international migration: The importance of the agricultural linkage. *Journal of Environmental Economics and Management*, **79**, 135–151.

Cattaneo, Cristina, Beine, Michel, Fröhlich, Christiane J, Kniveton, Dominic, Martinez-Zarzoso, Inmaculada, Mastrorillo, Marina, Millock, Katrin, Piguet, Etienne, & Schraven, Benjamin. 2019. Human migration in the era of climate change. *Review of Environmental Economics and Policy*, **13**(2), 189–206.

Colmer, Jonathan. 2021. Temperature, labor reallocation, and industrial production: Evidence from India. *American Economic Journal: Applied Economics*, **13**(4), 101–24.

Dean, Joshua T, & Jayachandran, Seema. 2019. Changing family attitudes to promote female employment. *Pages 138–42 of: AEA Papers and Proceedings*, vol. 109.

Dell, Melissa, Jones, Benjamin F, & Olken, Benjamin A. 2014. What do we learn from the weather? The new climate-economy literature. *Journal of Economic Literature*, **52**(3), 740–98.

Dillon, Andrew, Mueller, Valerie, & Salau, Sheu. 2011. Migratory responses to agricultural risk in northern Nigeria. *American Journal of Agricultural Economics*, **93**(4), 1048–1061.

Emerick, Kyle. 2018. Agricultural productivity and the sectoral reallocation of labor in rural India. *Journal of Development Economics*, **135**, 488–503.

Eswaran, Mukesh, Ramaswami, Bharat, & Wadhwa, Wilima. 2013. Status, caste, and the time allocation of women in rural India. *Economic Development and Cultural Change*, **61**(2), 311–333.

Giannelli, Gianna Claudia, & Canessa, Eugenia. 2022. After the flood: Migration and remittances as coping strategies of rural Bangladeshi households. *Economic Development and Cultural Change*, **70**(3), 1159–1195.

Grabrucker, Katharina, & Grimm, Michael. 2021. Is There a Rainbow after the Rain? How Do Agricultural Shocks Affect Non-Farm Enterprises? Evidence from Thailand. *American Journal of Agricultural Economics*, **103**(5), 1612–1636.

Gray, Clark, & Mueller, Valerie. 2012. Drought and population mobility in rural Ethiopia. *World development*, **40**(1), 134–145.

Gröger, André, & Zylberberg, Yanos. 2016. Internal labor migration as a shock coping strategy: Evidence from a typhoon. *American Economic Journal: Applied Economics*, **8**(2), 123–53.

Halliday, Timothy J. 2012. Intra-household labor supply, migration, and subsistence constraints in a risky environment: Evidence from rural El Salvador. *European Economic Review*, **56**(6), 1001–1019.

Heath, Rachel, & Mobarak, A Mushfiq. 2015. Manufacturing growth and the lives of Bangladeshi women. *Journal of Development Economics*, **115**, 1–15.

Hsiang, Solomon, & Kopp, Robert E. 2018. An economist's guide to climate change science. *Journal of Economic Perspectives*, **32**(4), 3–32.

Huang, Kaixing, Zhao, Hong, Huang, Jikun, Wang, Jinxia, & Findlay, Christopher. 2020. The impact of climate change on the labor allocation: Empirical evidence from China. *Journal of Environmental Economics and Management*, **104**, 102376.

IPCC. 2021. *Climate Change 2021*. Tech. rept. https://www.ipcc.ch/report/ar6/wg1/downloads/report/IPCC_AR6_WGI_SPM.pdf.

Ito, Takahiro, & Kurosaki, Takashi. 2009. Weather risk, wages in kind, and the off-farm labor supply of agricultural households in a developing country. *American Journal of Agricultural Economics*, **91**(3), 697–710.

Jayachandran, Seema. 2006. Selling labor low: Wage responses to productivity shocks in developing countries. *Journal of Political Economy*, **114**(3), 538–575.

Jayachandran, Seema. 2015. The Roots of Gender Inequality in Developing Countries. *Annu. Rev. Econ*, **7**, 63–88.

Jessoe, Katrina, Manning, Dale T, & Taylor, J Edward. 2018. Climate change and labour allocation in rural Mexico: Evidence from annual fluctuations in weather. *The Economic Journal*, **128**(608), 230–261.

Kala, Namrata. 2017. Learning, adaptation, and climate uncertainty: Evidence from Indian agriculture. *MIT Center for Energy and Environmental Policy Research Working Paper No. 23*.

Kochar, Anjini. 1999. Smoothing consumption by smoothing income: hours-of-work responses to idiosyncratic agricultural shocks in rural India. *Review of Economics and Statistics*, **81**(1), 50–61.

Kristjanson, Patricia, Bryan, Elizabeth, Bernier, Quinn, Twyman, Jennifer, Meinzen-Dick, Ruth, Kieran, Caitlin, Ringler, Claudia, Jost, Christine, & Doss, Cheryl. 2017. Addressing gender in agricultural research for development in the face of a changing climate: where are we and where should we be going? *International Journal of Agricultural Sustainability*, **15**(5), 482–500.

Liu, Maggie Y, Shamdasani, Yogita, & Taraz, Vis. 2021. Climate change and labor reallocation: Evidence from six decades of the Indian Census. *Forthcoming, American Economic Journal: Economic Policy*.

Mahajan, Kanika. 2017. Rainfall shocks and the gender wage gap: Evidence from Indian agriculture. *World Development*, **91**, 156–172.

Maitra, Pushkar, & Tagat, Anirudh. 2019. Labour Supply Responses to Rainfall Shocks. *Available at SSRN 3449144*.

Marchiori, Luca, Maystadt, Jean-François, & Schumacher, Ingmar. 2012. The impact of weather anomalies on migration in sub-Saharan Africa. *Journal of Environmental Economics and Management*, **63**(3), 355–374.

Minale, Luigi. 2018. Agricultural productivity shocks, labour reallocation and rural–urban migration in China. *Journal of Economic Geography*, **18**(4), 795–821.

Morduch, Jonathan. 1995. Income smoothing and consumption smoothing. *Journal of Economic Perspectives*, **9**(3), 103–114.

Morten, Melanie. 2019. Temporary migration and endogenous risk sharing in village india. *Journal of Political Economy*, **127**(1), 1–46.

Mueller, Valérie A, & Osgood, Daniel E. 2009. Long-term impacts of droughts on labour markets in developing countries: Evidence from Brazil. *The Journal of Development Studies*, **45**(10), 1651–1662.

Pachauri, Rajendra K, Allen, Myles R, Barros, Vicente R, Broome, John, Cramer, Wolfgang, Christ, Renate, Church, John A, Clarke, Leon, Dahe, Qin, Dasgupta, Purnamita, *et al.* . 2014. *Climate change 2014: synthesis report. Contribution of Working Groups I, II and III to the fifth assessment report of the Intergovernmental Panel on Climate Change*. IPCC.

Rose, Elaina. 2001. Ex ante and ex post labor supply response to risk in a low-income area. *Journal of Development Economics*, **64**(2), 371–388.

Sabarwal, Shwetlena, Sinha, Nistha, & Buvinic, Mayra. 2011. How Do Women Weather Economic Shocks? What We Know. *World Bank-Economic Premise 46*, 1–6.

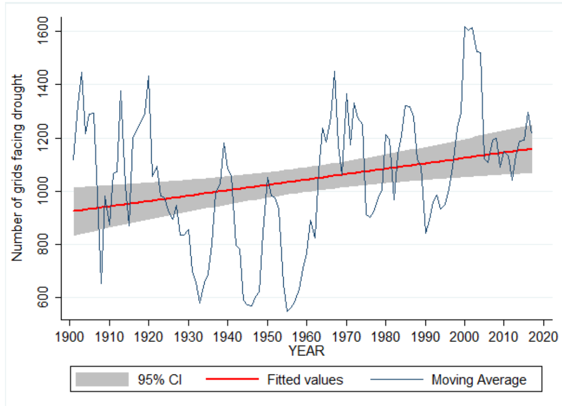
Schiermeier, Quirin. 2018. Droughts, heatwaves and floods: How to tell when climate change is to blame. *Nature*, **560**(7717), 20–23.

Skoufias, Emmanuel, & Parker, Susan W. 2006. Job loss and family adjustments in work and schooling during the Mexican peso crisis. *Journal of Population Economics*, **19**(1), 163–181.

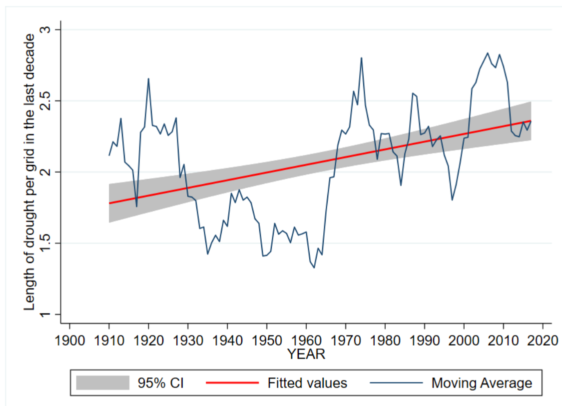
Taraz, Vis. 2017. Adaptation to climate change: Historical evidence from the Indian monsoon. *Environment and Development Economics*, **22**(5), 517–545.

Turner, Andrew G, & Annamalai, Hariharasubramanian. 2012. Climate change and the South Asian summer monsoon. *Nature Climate Change*, **2**(8), 587–595.

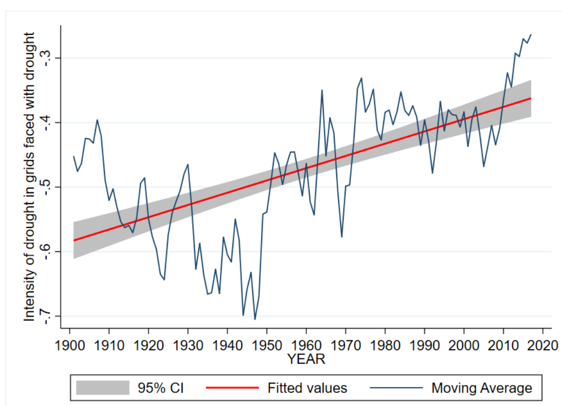
Figure 1: Frequency, Duration and Intensity of Droughts in India (1901-2017)



(a) Frequency



(b) Duration



(c) Intensity

Source: IMD data (1901-2017)
Note: A drought is defined to occur when the monsoon rainfall in a grid lies in the bottom two deciles of the long-run distribution (1901-2017). Figure (a) plots the five-year moving average of the *Frequency of droughts*. Figure (b) plots the duration as measured by the *Length of drought* – the average number of drought years in each grid experienced in the preceding decade. Figure (c) plots the five-year moving average of *Intensity of drought* – the standard deviation of monsoon rainfall in a grid from its long-run average during the drought year.

Table 1: 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	134721	0.69	0.46	145214	0.92	0.26
Employed	134721	0.68	0.47	145214	0.92	0.27
Unemployed	134721	0.06	0.24	145214	0.10	0.30
Paid farm	134721	0.18	0.38	145214	0.12	0.33
Family farm	134721	0.36	0.48	145214	0.50	0.50
Family livestock	134721	0.42	0.49	145214	0.44	0.50
Non-farm	134721	0.12	0.33	145214	0.47	0.50
Panel B: Workdays per month						
Labor force days	134721	12.82	13.15	145214	22.65	13.85
Employed days	134721	12.23	12.65	145214	21.65	13.36
Unemployed days	134721	0.58	3.08	145214	1.00	3.98
Paid farm days	134721	2.39	5.77	145214	1.74	5.27
Family farm days	134721	2.45	4.41	145214	4.40	6.35
Family livestock days	134721	4.88	9.12	145214	5.26	9.19
Non-farm days	134721	2.51	7.33	145214	10.26	12.11
Unskilled	134721	0.41	3.06	145214	2.54	7.08
Skilled	134721	0.63	3.77	145214	2.82	7.65
Business/Salaried	134721	1.23	5.45	145214	4.67	10.10
Panel C: Real wage earnings per month (Rs.)						
Paid farm earnings	134721	37.10	98.16	145214	41.89	182.24
Non-farm earnings	134721	56.46	263.89	145214	448.76	1012.95
Paid farm earnings (Conditional)	23692	210.95	134.61	17712	343.37	410.80
Non-farm earnings (Conditional)	16692	447.03	601.96	67554	956.24	1304.41
Farm wage rates	23692	15.56	6.34	17712	23.34	16.96
Non-farm wage rates	16692	21.14	23.41	67554	43.41	76.68
Panel D: Workplace in a month						
Within village	134721	0.25	0.43	145214	0.29	0.45
Outside Village	134721	0.04	0.20	145214	0.29	0.46
Migration	134721	0.02	0.12	145214	0.13	0.33
Distance to work (kms.)	134721	77.10	1170.99	145214	2179.13	9156.47
Distance to work excluding migrants (kms.)	132649	5.63	135.89	126736	105.49	1351.05
Panel E: Non-farm workdays by demographic groups						
Young	76652	2.60	7.47	83376	12.14	12.39
Older	58069	2.40	7.13	61838	7.73	11.24
Married	102630	2.48	7.20	101175	10.42	12.03
Unmarried	32091	2.63	7.72	44039	9.87	12.30
Parent	36431	2.19	6.69	36237	12.91	12.07
Non-Parent	98290	2.63	7.55	108977	9.38	12.00

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

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*	0.005	0.016*	-0.016
	(0.007)	(0.003)	(0.006)	(0.003)	(0.008)	(0.010)
Difference	-0.012**		-0.017***		0.032***	
	(0.006)		(0.005)		(0.009)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
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	-0.081	0.026	-0.153**	0.036	0.144*	-0.150*
	(0.082)	(0.047)	(0.073)	(0.048)	(0.079)	(0.089)
Difference	-0.107*		-0.190***		0.294***	
	(0.059)		(0.055)		(0.082)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.679	0.642	0.675	0.628	0.330	0.369
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 B.2 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 annual trends) 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	-0.009	-0.003	0.005	-0.016***	-0.011	-0.002	-0.016*	0.003	0.003	0.021***
	(0.010)	(0.008)	(0.005)	(0.006)	(0.010)	(0.008)	(0.009)	(0.009)	(0.006)	(0.005)
Difference	-0.005		0.021***		-0.009		-0.019**		-0.018***	
	(0.008)		(0.007)		(0.008)		(0.009)		(0.007)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.603	0.582	0.611	0.519	0.596	0.598	0.681	0.669	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	-0.052	-0.068	0.016	-0.137**	-0.053	-0.039	-0.210***	-0.020	0.024	0.225***
	(0.092)	(0.079)	(0.051)	(0.058)	(0.086)	(0.073)	(0.080)	(0.074)	(0.066)	(0.061)
Difference	0.016		0.153**		-0.015		-0.189**		-0.201***	
	(0.076)		(0.065)		(0.077)		(0.085)		(0.071)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.615	0.613	0.623	0.527	0.605	0.632	0.678	0.687	0.629	0.704
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 B.2. 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 annual trends) 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	0.005	-0.185***	-0.010	0.175**	-0.381***	-0.034	-0.100	-0.090**	-0.114***	0.036	-0.073	-0.081***
	(0.056)	(0.064)	(0.072)	(0.075)	(0.079)	(0.106)	(0.092)	(0.040)	(0.037)	(0.059)	(0.048)	(0.029)
Difference	0.189**		-0.186**		-0.347***		-0.010		-0.151**		0.008	
	(0.073)		(0.085)		(0.119)		(0.083)		(0.065)		(0.051)	
Observations	134,709	145,202	134,709	145,202	23,647	17,627	16,645	67,809	23,647	17,627	16,645	67,809
R-squared	0.622	0.526	0.642	0.723	0.425	0.498	0.725	0.728	0.619	0.628	0.777	0.781
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 in a given sector) 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 B.2 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 annual trends) and village level time-varying indicator variable for upper two deciles of monsoon rainfall. In columns (5)-(6), we only include the interaction of wealth in the first year of the survey with annual trends and drop the interaction with assets because of singularity of the variance matrix. 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	-0.200**	-0.004	-0.015	-0.155**	-0.035	-0.029	-0.257***	-0.053	0.029	0.178***
	(0.084)	(0.047)	(0.056)	(0.070)	(0.094)	(0.072)	(0.096)	(0.085)	(0.077)	(0.061)
Difference	-0.196***		0.140*		-0.007		-0.205**		-0.149*	
	(0.066)		(0.075)		(0.080)		(0.097)		(0.078)	
Observations	97,025	109,295	97,025	109,295	97,025	109,295	97,025	109,295	97,025	109,295
R-squared	0.644	0.525	0.627	0.522	0.603	0.636	0.669	0.693	0.627	0.700
Panel B: Unconditional Sample										
Drought	-0.107	0.028	0.020	-0.141**	-0.038	-0.053	-0.170**	-0.033	0.033	0.234***
	(0.076)	(0.053)	(0.050)	(0.056)	(0.083)	(0.073)	(0.080)	(0.075)	(0.064)	(0.057)
Difference	-0.135**		0.160**		0.015		-0.137		-0.202***	
	(0.059)		(0.063)		(0.075)		(0.089)		(0.065)	
Observations	140,184	151,608	140,184	151,608	140,184	151,608	140,184	151,608	140,184	151,608
R-squared	0.652	0.592	0.615	0.520	0.601	0.627	0.662	0.670	0.607	0.683
Panel C: Village-specific annual trends										
Drought	-0.129*	0.021	-0.017	-0.067	-0.056	-0.005	-0.123*	-0.107*	0.002	0.136**
	(0.074)	(0.038)	(0.046)	(0.048)	(0.081)	(0.077)	(0.070)	(0.056)	(0.057)	(0.054)
Difference	-0.149***		0.051		-0.051		-0.015		-0.134**	
	(0.056)		(0.065)		(0.051)		(0.062)		(0.064)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.680	0.633	0.628	0.533	0.615	0.639	0.685	0.696	0.632	0.708
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 B.2 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 annual trends) 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	0.004	-0.010	-0.000	0.017***	0.001	0.008**	-0.012	0.199***
	(0.006)	(0.006)	(0.003)	(0.006)	(0.001)	(0.003)	(0.028)	(0.074)
Difference	0.014**		-0.018***		-0.007**		-0.211***	
	(0.007)		(0.006)		(0.003)		(0.071)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.659	0.603	0.588	0.675	0.643	0.721	0.606	0.701
Mean Y	0.25	0.29	0.04	0.29	0.02	0.13	77.10	2179.13
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 annual trends) 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	0.108	0.218***	-0.009	0.175	0.080	0.229***
	(0.070)	(0.059)	(0.081)	(0.116)	(0.070)	(0.065)
(B) Z x Drought	-0.146**	0.014	0.043	0.070	-0.214**	-0.020
	(0.059)	(0.088)	(0.079)	(0.120)	(0.085)	(0.107)
Difference (A)	-0.109		-0.184		-0.149	
	[0.14]		[0.07]		[0.04]	
Difference ((A)+(B))	-0.27		-0.212		-0.343	
	[0]		[0.02]		[0.01]	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.629	0.704	0.629	0.704	0.629	0.704
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 15-39 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 annual trends) 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	0.000	0.005*	0.001	-0.000	0.001	0.004
	(0.001)	(0.003)	(0.002)	(0.007)	(0.001)	(0.004)
(B) Z x Drought	0.001	0.005	-0.001	0.011	-0.002	0.018**
	(0.002)	(0.006)	(0.002)	(0.009)	(0.003)	(0.008)
Difference (A)	-0.005		0.002		-0.002	
	[0.09]		[0.83]		[0.49]	
Difference ((A)+(B))	-0.009		-0.011		-0.023	
	[0.09]		[0.01]		[0]	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.643	0.721	0.643	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 15-39 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 annual trends) 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	0.002	0.106**	0.029	0.061	-0.038	0.039
	(0.017)	(0.047)	(0.030)	(0.044)	(0.040)	(0.036)
Difference	-0.104**		-0.032		-0.078	
	(0.044)		(0.050)		(0.048)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.448	0.585	0.558	0.644	0.654	0.711
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 annual trends) 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 profit maximizing equilibrium labor demand with the farm production function as specified in Eq. (3) is given by:

$$L_a = \left(\frac{\theta B^{\epsilon} - \theta \epsilon B^{\epsilon}}{w_a} \right)^{1/\epsilon} \tag{A.7}$$

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

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

$$u_n - p\Psi = 0 \tag{A.9}$$

$$u_{l_a} - \Psi w_a = 0 \tag{A.10}$$

$$u_{l_n} - v_{l_n} - \Psi w_n = 0 \tag{A.11}$$

Total differentiation of equations (A.8) through (A.11) and (2) yields:

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

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:

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

$$\frac{dl_{am}}{dD} = \left(\frac{dl_{am}}{dw_a}\right) \times \left(\frac{dw_a}{dD}\right) = \left(\frac{R}{H}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{A.14}$$

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

$$\frac{dl_{nm}}{dD} = \left(\frac{dl_{nm}}{dw_a}\right) \times \left(\frac{dw_a}{dD}\right) = \left(\frac{J}{H}\right) \times \left(-\frac{dw_a}{dD}\right) \tag{A.16}$$

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:

$$\begin{aligned}
J &= w_n(l_1(-u_{11}u_{22}u_{33} + u_{11}{u_{23}}^2 + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22}) \\
&\quad + \psi(-pu_{11}u_{23} + pu_{12}u_{13} + u_{12}u_{23} - u_{13}u_{22})) \\
&\quad + w_a(\psi(-pu_{11}u_{23} + pu_{12}u_{13} + w_n(u_{11}u_{22} - {u_{12}}^2) + u_{12}u_{23} - u_{13}u_{22}) \\
&\quad - l_1(-u_{11}u_{22}u_{33} + u_{11}{u_{23}}^2 + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22})) \\
&\quad + \psi(u_{33}(p^2u_{11} - 2pu_{12} + u_{22}) - (u_{23} - pu_{13})^2) \\
H &= (w_a - w_n)^2(u_{11}({u_{23}}^2 - u_{22}u_{33}) + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22}) \\
Z &= v_{11}(u_{33}(p^2u_{11} - 2pu_{12} + u_{22}) + 2w_a(-pu_{11}u_{23} + pu_{12}u_{13} + u_{12}u_{23} - u_{13}u_{22}) \\
&\quad - (u_{23} - pu_{13})^2 + w_a^2(u_{11}u_{22} - {u_{12}}^2)) \\
R &= l_1(w_a - w_n)(-u_{11}u_{22}u_{33} + u_{11}{u_{23}}^2 + {u_{12}}^2u_{33} - 2u_{12}u_{13}u_{23} + {u_{13}}^2u_{22}) \\
&\quad + \psi(-u_{33}(p^2u_{11} - 2pu_{12} + u_{22}) + 2w_n(pu_{11}u_{23} - pu_{12}u_{13} - u_{12}u_{23} + u_{13}u_{22}) \\
&\quad + (u_{23} - pu_{13})^2 + w_n^2({u_{12}}^2 - u_{11}u_{22})) \\
S &= v_{11}(l_1(-pu_{11}u_{23} + pu_{12}u_{13} + w_a(u_{11}u_{22} - {u_{12}}^2) + u_{12}u_{23} - u_{13}u_{22}) \\
&\quad + \psi(p^2u_{11} - 2pu_{12} + u_{22}))
\end{aligned} \tag{A.17}$$

Using equation (A.16), the conditions under which men diversify to the non-farm sector due to a drought are as follows:

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

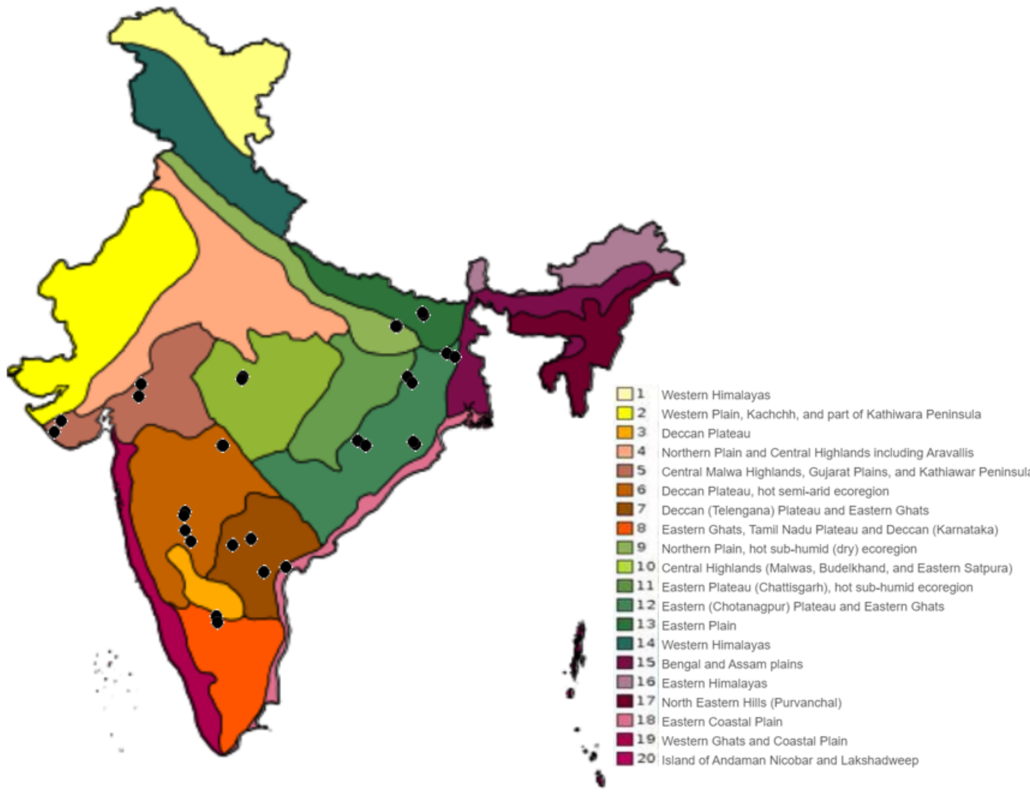
Using equations (A.15) and (A.16), the conditions for a negative gender differential in non-farm employment due to a drought i.e., women diversify less to the non-farm sector relative to men due to a drought, are given by:

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

And the converse holds otherwise.

B Additional Analyses, Tables and Figures

Figure B.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).

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 below the age of 10 years, 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)

Variable	N	Mean	S.D.	Definition
Panel A: Labor market participation per month (Extensive margin)				
Labor force	279935	0.81	0.39	=1 if employed or sought work, 0 otherwise
Employed	279935	0.80	0.40	=1 if worked for a positive number of days, 0 otherwise
Unemployed	279935	0.08	0.27	=1 if sought work for a positive number of days, 0 otherwise
Paid farm	279935	0.15	0.36	=1 if worked for a positive number of days in paid farm work, 0 otherwise
Family farm	279935	0.43	0.49	=1 if worked for a positive number of days in family farm work, 0 otherwise
Family livestock	279935	0.43	0.50	=1 if worked for a positive number of days on family livestock, 0 otherwise
Non-farm	279935	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	279935	17.92	14.38	number of days worked or seeking work
Employed days	279935	17.12	13.85	number of days worked (farm plus non-farm)
Unemployed days	279935	0.80	3.58	number of days spent seeking work
Paid farm days	279935	2.05	5.52	number of days worked in paid farm
Family farm days	279935	3.46	5.59	number of days worked in family farm
Family livestock days	279935	5.08	9.16	number of days worked on family livestock
Non-farm days	279935	6.53	10.81	number of days worked in non-farm
Panel C: Real wage earnings per month (Rs.)				
Paid farm earnings	279935	39.58	147.89	real earnings from paid farm work, 0 if unemployed or not working in paid farm
Non-farm earnings	279935	259.96	777.30	real earnings from non-farm work, 0 if unemployed or not working in non-farm
Paid-farm earnings(Conditional)	41401	267.60	297.71	real earnings from farm work if working in paid farm work in that month, missing otherwise
Non-farm earnings(Conditional)	84215	855.71	1215.81	real earnings from non-farm work if working in non-farm work in that month, missing otherwise
Farm wage rate	41401	19.32	12.84	earnings per work day in paid farm in a month
Non-farm wage rate	84215	39.01	70.04	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.

Validity of Drought Measure:

We confirm that our measure of drought accurately captures the scarcity of water resulting from low rainfall in Table B.3 below. The farm productivity is negatively affected as indicated by the 56.1% (column (1)) fall in production and 33.2% (column (2)) reduction in yield of rice in a drought year. The average farm revenue of a household falls by 27.7% (column (3)), although imprecise, while profits fall significantly by 49.5% due to drought (column (4)).

Additionally, Table B.4 reports a reduction in the total labor use on-farm by 24% (column (1)). Since the preparation of land is the first operation to be performed at the start of the agriculture season, tasks 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. 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 4-5%. The requirement for weeding and harvesting labor falls during a drought by 84.2% (column (4)) and 50.3% (column (5)), respectively, as yields plummet and additionally, weed growth gets stunted due to low rainfall. We find similar results when we consider per-acre labor usage hours as the dependent variable.

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*	-0.277	-0.495***
	(0.256)	(0.181)	(0.191)	(0.171)
Observations	114	114	11,606	11,606
R-squared	0.865	0.720	0.383	0.438
Mean Y	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 Y' 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 annual trends) 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	-0.240***	-0.050	-0.043	-0.842***	-0.503*
	(0.082)	(0.156)	(0.177)	(0.305)	(0.284)
Observations	8,657	8,657	8,657	8,657	8,657
R-squared	0.569	0.484	0.559	0.519	0.380
Mean Y	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 Y' 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 annual trends) and village time-varying indicator variable for upper two deciles of monsoon rainfall. Standard errors clustered at village-season level are reported in parentheses (*** $p<0.01$, ** $p<0.05$, * $p<0.1$).

Effect of Drought on Intensive Margin of Work: 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. Similar to the results for extensive margin and workdays, we find that women's hours, relative to men's, in paid farm increase by 13.1% (columns (3)-(4)) but contract in non-farm by 18.7% (columns (5)-(6)).

Table B.5: Effect of Drought on Hours of Work

	Paid Farm + Non-farm		Paid Farm		Non-farm	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)
Drought	0.004	0.084	0.017	-0.113**	0.012	0.198***
	(0.064)	(0.074)	(0.049)	(0.055)	(0.058)	(0.061)
Difference	-0.080		0.131**		-0.187***	
	(0.071)		(0.061)		(0.068)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.692	0.705	0.623	0.523	0.626	0.708
Mean Y	32.75	93.27	17.53	13.01	15.23	80.26
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 (paid farm+non-farm) activities, paid farm activities and non-farm activities by an individual in a given month in columns (1)-(2), (3)-(4) and (5)-(6), respectively. 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 annual trends) 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 Specifications)

	Lagged shocks				Temperature and its square			
	Paid Farm		Non-farm		Paid Farm		Non-farm	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)
Drought	0.011	-0.179***	0.048	0.211***	0.006	-0.139*	-0.006	0.230***
	(0.058)	(0.066)	(0.081)	(0.073)	(0.066)	(0.076)	(0.088)	(0.071)
Lag Drought	0.100	0.011	-0.008	-0.141*				
	(0.064)	(0.066)	(0.053)	(0.079)				
Temp					0.002	0.006	0.005	-0.005
					(0.003)	(0.004)	(0.004)	(0.003)
$Temp^2$					-0.000	-0.000**	-0.000	0.000*
					(0.000)	(0.000)	(0.000)	(0.000)
Difference	0.190***		-0.163*		0.145*		-0.237***	
	(0.069)		(0.093)		(0.078)		(0.082)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.624	0.527	0.629	0.704	0.623	0.527	0.629	0.704
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. All the specification in columns (1)-(8) are the same as our main specification and additionally control for a one year lag of drought and flood (columns (1)-(4)), and quadratic form of temperature shock in column (9)-(12). The temperature shock measures Harmful Degree Days (HDDs) during the monsoon season defined as the sum of the deviations of daily maximum temperature above the median of its long-run village-level monthly maximum temperature over the monsoon period. The first row reports the regression coefficients for drought while the second row reports the estimates for one year lagged drought shock followed by temperature and temperature square and the last 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 annual trends) 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 (Alternative Measures of Drought)

	Drought Measure 1				Drought Measure 2			
	Paid Farm		Non-farm		Paid Farm		Non-farm	
	Female (1)	Male (2)	Female (3)	Male (4)	Female (5)	Male (6)	Female (7)	Male (8)
Drought	0.002	0.049	-0.023	0.101**	-0.000	-0.003***	-0.000	0.003**
	(0.040)	(0.040)	(0.034)	(0.048)	(0.001)	(0.001)	(0.001)	(0.001)
Difference	-0.047		-0.124***		0.003***		-0.003**	
	(0.047)		(0.042)		(0.001)		(0.001)	
Observations	134,709	145,202	134,709	145,202	134,709	145,202	134,709	145,202
R-squared	0.623	0.526	0.629	0.704	0.623	0.527	0.629	0.704
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. In columns (1)-(4), 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 (5)-(8) is the Harmful Degree Days (HDDs) during the monsoon season defined as the sum of the deviations of daily maximum temperature above the median of its long-run village-level monthly maximum temperature over the monsoon period. 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 annual trends) 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.8: Effect of Drought on Workdays: Robustness (NSS data)

	Farm		Non-farm	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
Drought	-0.121***	-0.083**	-0.003	0.097***
	(0.041)	(0.036)	(0.022)	(0.030)
Difference (Drought)	-0.038		-0.100***	
	(0.046)		(0.030)	
Observations	430,905	434,566	430,905	434,566
R-squared	0.186	0.147	0.079	0.150
Mean Y	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.9: Effect of Drought on NREGS days

	VDSA		NREGS Portal	
	Female	Male	Female	Male
	(1)	(2)	(3)	(4)
Drought	0.127	0.011	0.370***	0.335***
	(0.157)	(0.276)	(0.074)	(0.073)
Difference	0.115		0.035*	
	(0.243)		(0.019)	
Observations	5,195	5,641	405,105	405,105
R-squared	0.640	0.521	0.700	0.697
Mean Y	3.6	3.39	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 annual trends) 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.10: 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	-0.028	0.066	-0.031	0.066
	(0.026)	(0.043)	(0.026)	(0.043)
(B) Z x Drought	0.059	0.057	0.063	0.058
	(0.043)	(0.059)	(0.043)	(0.059)
Difference (A)	-0.094		-0.097	
	[0.03]		[0.02]	
Difference ((A)+(B))	-0.092		-0.092	
	[0.03]		[0.03]	
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).