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Agricultural Productivity Shocks, Labor Reallocation, and Rural-Urban Migration in China[1]

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Abstract

This paper analyses the way households in rural China use rural-urban migration and off-farm work as a response to negative productivity shocks in agriculture. I employ various waves of a longitudinal survey to construct a panel of individual migration and labour supply histories, and match them to detailed weather information, which I use to instrument agricultural productivity. For identification, I exploit the year-by-county variation in growing season rainfalls to explain within-individual changes in labor allocation. Data on days of work supplied to each sector allow to study the responses to weather shocks along both the participation and the intensive margin. Results suggest that farming is reduced by 4.5% and migration increased by about 5% in response to a 1-standard deviation negative rainfall shock. Increase in rural-urban migration derives from both longer spells in the city and from increment in the likelihood to participate in the urban sector. I find interesting heterogeneous response across generations driven by age-specific productivities in the different sectors and migration costs. Finally, land tenure insecurity seems to partially prevent households from freely reallocating labor away from farming in bad times.

Keywords: Agricultural productivity; Labor supply; Rural-urban migration; China.

Codes: J22; R23; J61

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1. Introduction

Rural households in developing countries, by relying mainly on agricultural activity, face substantial idiosyncratic and common risk, which can result in high income variability. Furthermore, due to imperfect insurance and credit markets, their ability to smooth consumption and insure against adverse events is typically limited; and since many households live close to, or below, the poverty line, failure to cope with shocks can have negative impacts on nutrition, health, mortality rate, and translate into persistent poverty[2]. In order to cope with negative economic shocks, in the absence of adequate markets, households have developed a number of strategies as risk sharing (Rosenzweig and Stark, 1989; Townsend, 1994); self-insurance and precautionary savings (Rosenzweig and Wolpin, 1993); asset depletion and disinvestment in education (Udry, 1995; Thomas et al., 2004) and ganyu labor arrangaments (Kerr, 2005). All these mechanisms have received quite extensive attention. Yet, another way through which households can smooth consumption is by smoothing income (Kochar, 1999; and Rose, 2001). In other words, individuals can respond to negative productivity shocks in agriculture by temporary shifting the labour supply across sectors and locations. To the extent that non-agricultural labour market and own-farm productivity are not perfectly correlated, indeed, supply of labour to the local non-agricultural sector, as well as to the urban one, are two means that households can use in order to cope with negative agricultural productivity shocks.

The use of labour markets to smooth income has been, relatively to other potential coping mechanisms, under-researched. However, it is of great importance for economists and policy makers to understand how labour market opportunities and institutions help poor households to smooth income and consumption when their primary source of income is under threat. Understanding such mechanisms is even more relevant nowadays in light of the effects that climate change is believed to be inducing (Dell et al., 2014). Indeed, scientists expect the size and frequency of extreme weather events, concerning both rainfalls and temperature, to increase due to the climate change.

[2] Maccini and Yang (2009) for instance show that income shocks, even temporary ones, can have sizable negative long-term consequences on education, health, and labour market outcomes.

The research question this paper wants to answer is if, and in what measure, individuals and households in rural China reallocate labour across sectors – away from farming and toward local off-farm and rural-urban migration - as a response to negative productivity shocks in agriculture. There are a number of reasons why it is relevant to study this topic in China. First, despite the outstanding growth record that China has enjoyed during the last two decades, many are still those left behind, especially in rural areas where half of the population, and about 90%-95% of all the poor, reside (World Bank). Agriculture is still the most important source of income in most rural areas, and weather is responsible for about 25-30% of the annual variation in agricultural production (Zhang & Carter, 1997). Second, China is characterised by high rates of internal mobility, with estimates of about 277.5 million of rural migrants working in Chinese cities by year 2015 (NBS, 2016)[3]. Migration is mostly temporary, also because of restrictions to permanent change of residence such as the *houku* system. According to RUMiC Survey almost one out of three individuals aged 16-65 spent some time working in the city between year 2008 and 2010. Of them, a 33% reported to have been working in both the home village and the city of destination during the same year; while in 70% of the cases the length of time spent working in the city differs between two consecutive years[4]. According to these data, rural-urban migrants are a very mobile population, so called *floating population*. I will show that some of this migration can be explained as an optimal response to shocks in the productivity of the main agricultural sector.

The paper uses data from a longitudinal household survey conducted in rural China between 2008 and 2011 to relate changes in days of work supplied to each of three different activities - farming, off-farm work in the home village, and rural-urban migration - with weather shocks affecting agricultural productivity at the county level. I focus on rainfalls as they have been shown to the relevant determinants of agricultural productivity in China, especially for rice cultivation (Shili, 2005), but results are robust to the inclusion of temperature data[5]. For identification, I exploit the plausible exogenous year-to-year variation in growing season rainfalls at the county level, which

[3] Of them, 109 milion are considered short-distance migrants (workers who moved within their province of origin) and the remaining 169 are long-distance migrants (outside their province of origin).
[4] Interestingly enough, there is large variability in the share of time over the year spent in the city both in the cross sectional and in the time dimension. In an average year, 42% of rural-urban migrants (i.e. individuals who have spent a positive number of days working in the city) spend less than 300 days working in the city, and 18% spend less than 200 days.
[5] Jiles (2006) also underlines the relevance of rainfall shocks for rural Chinese households and the importance of the opening up of rural labour markets to provide new margins of income smoothing.

is generated by the Chinese peculiar size and climatic heterogeneity, and match it to over-time variation in labour supplied by individuals to each of the sectors. The inclusion of individual and time fixed effects should insure that local weather shocks are orthogonal to unobserved factors affecting individual labour allocation choices.

I find that negative (positive) shocks of growing season rainfalls are associated with less (more) farming and more (less) rural-urban migration. By using detailed data on the number of days of work supplied to each activity during the past year, I am able to study the responses to weather shocks along both the participation and the intensive margin. I find that yearly working days devoted to farming drop by 4.5% while those spent working in the urban sector increase by 4.9% in correspondence to mild negative rainfall shocks, i.e. rainfall realisation 1 standard deviation below the long-term average. The increase in number of days individuals spend working in the city derives from both longer spells in the city for those already engaging in urban work (intensive margin) and from increase in the likelihood to participate at all in the urban sector (extensive margin), which increases by 2.1% on the baseline value. Next, I find interesting heterogeneous response across generations driven by age specific productivities in the urban sector and costs of leaving (even temporarily) the home village. While younger individuals tend to shift labour supply from farming toward working in the city, older individuals generally shift labour from farming toward local off-farm work, without leaving the home village. At the household level, I estimate that in correspondence with mild negative shock households reduce the total labour supply to the farming sector by about 2.1% and reallocate it almost entirely to the urban sector. I also show that households with little irrigation seem to be more exposed to weather fluctuations and more responsive to shocks. Finally, I look at the interplay between land reallocation risk and propensity to move labour from farming toward rural-urban migration in bad years. Results suggest that the elasticity of rural-urban migration to agricultural productivity in villages with high risk of land reallocation is about half the size of that in other villages.

This paper contributes to the traditional literature studying labour supply as response to income shocks as well as to the more recent one looking at the effects of weather events on migration. The first group of papers mainly looks at how households respond to income shocks by increasing off-farm labour (see for example Kochar, 1999; and Rose, 2001)[6]; I contribute to it by extending the analysis to internal migration as a further margin of adjustment, and considering both mobility between occupations and between locations within the same framework. Indeed, when a shock is aggregate in its nature, migration is likely to be an optimal response, and a fast growing literature is investigating precisely such relation between weather shocks and emigration (see, among the others, Munshi, 2003; Barrios et al. 2006; Gray and Mueller, 2012; Marchiori et al., 2012; Jessoe et al., 2016; Mueller et al., 2017; and Dell et al. (2014) for a broader literature review). Particularly close to this paper is the one from Jessoe et al (2016) that investigates the impact of weather variations on labour allocation, including migration, using data on sectoral participation in Mexico. I extend on this literature by studying not only the participation but also the intensive margin of response to weather variations. Indeed, the availability of data about the number of days supplied to each sector enables me to detect responses to weather shocks that occur even without movements along the participation margin.

The rest of the paper is organised as follows: section 2 presents the theoretical framework; section 3 introduces the data and some descriptive statistics; section 4 describes the empirical strategy; section 5 discusses the results and section 6 concludes.

2. Agricultural Productivity Shocks and Labour Reallocation

In this section, I present an intuitive argument highlighting the relationship between weather shocks and labour allocation through the effect of the first on the relative productivity of work across activities. I will start by assuming that each individual has an endowment of labour and has to decide how to allocate it across different sectors in order to maximise utility. The three options are farm sector (farm work in or outside the family plot), local off-farm sector within the home village, and work in the urban sector (rural-urban migration).

Individuals decide upon the allocation of labour across the three sectors based on utilities that working in each of the sectors provide to them. Such utilities are a function of the relative

[6] Kochar (1999) and Rose (2001). The first one makes use of self-reported information on crop losses, included in the ICRISAT dataset from India, to analyse how households respond to shocks by increasing off-farm labour. The second one uses district level rainfall as measure of aggregate shocks and looks at how households change their labour force participation

productivity of labour in each sector, as well as of other factors such as entry costs, individual preferences, etc. If weather shocks differentially affect the productivity of labour across sectors, then individuals might respond by optimally re-allocating time between them. Agriculture productivity has been proven to depend on rainfall annual fluctuations, especially in a context where irrigation is only partially available. A decrease in farm income might cause a productivity drop also in the local off-farm sector, because of the induced decline in demand for non-agricultural goods and in services produced locally. Although, the productivity would decline less than in the agricultural sector. Finally, the productivity in the urban sector is the one that plausibly least depends on rainfalls, since weather should not directly affect economic activity in the city. As an extreme, exemplifying case, elasticity of urban productivity can be though to be zero in the absence of general equilibrium effects.

Utility of working in each one of the sectors, as a function of an agriculture-adverse rainfall shock (a negative deviation of agriculture-relevant rainfalls from the long-term average) is presented in panel A of Figure 1. In presence of adverse weather shocks households can find optimal to shift some labour from the most affected sector, farming, toward off-farm and urban work. It is important to underline that individual heterogeneity in, for instance, migration costs or productivity in the different sectors will cause the intercept of the curves in Figure 1 panel A, as well as their slopes, to vary. Panel B of Figure 1 shows the case where for certain individuals working off-farm delivers higher utility to start with, i.e. even for zero levels of adverse rainfall shocks. To conclude, the hypothesis we want to test are that in presence of a negative rainfall shock the time devoted to farming decreases while engagement in rural-urban migration increases. As far as time allocated to local off-farm sector is concerned the effect is unclear as in presence of such shocks, the productivity in the off-farm sector might increase vis-à-vis farming but decreasing vis-à-vis rural-urban migration. Thus, the response might differ across individuals and the net effect depends on the relative weights of different group of individuals in the population.

3. Data and Descriptive Statistics

3.1 Data

Labour supply. This paper uses data from the Rural Household Survey (RHS) of the Rural-Urban Migration in China (RUMiC) project (henceforth RUMiC-RHS). RUMiC began in 2008 and it conducts yearly longitudinal surveys of rural, urban, and migrant households. The RUMiC-RHS covers 82 counties (around 800 villages) in 9 provinces and is representative of the populations of these regions. A map of RUMiC-RHS surveyed provinces is proposed in Figure 2. The survey was conducted for 4 years and administered by China's National Bureau of Statistics and includes a rich set of individual and household level variables. I use information from the 2009, 2010 and 2011 rounds of the survey as they contain detailed information about the number of working days individuals devote to each specific sector. In particular, the survey asks the number of days the individual has dedicated, during the previous calendar year, to each of the following alternative occupations: 1) *farm work*; 2) *local* (within local countryside) *off-farm work*; and 3) *work in urban area*, i.e. outside local countryside. The fact that labour supply information are recorded every year, instead of at the end of a longer period, reduces the potential recall-bias issue. RUMiC-RHS survey includes 18,910 individuals in the labour force (aged between 16 and 65 and not currently at school or disabled) who provide information about age, gender, educational level and days devoted to each of the above alternative sectors in at least two of the three survey rounds between 2009 and 2011. Out of the 18,982 individuals above, complete labour supply information in each and every year is reported by 10,631 individuals, and in two of the three years by the rest of them (8,351), producing an estimating sample of 48,595 individual-year observations. For the part of the analysis at the household level, in order to keep the composition of household members reporting labour supply data fixed over time, I focus on those individuals who have reported labour supply information for all three years, from 2008 to 2010. That leaves me with a balanced panel of 3,794 households, corresponding to 11,382 household-year observations.

Weather shocks. I use detailed, county specific, information about daily rainfall to proxy agricultural productivity shocks. Daily precipitation data come from the Chinese National Ground Surface Dataset (GNGSD) provided by the Chinese National Meteorological Information Centre. Precipitation data are matched to counties in the RUMiC-RHS survey using the distance between the closest weather station and the centroid of each county. Instead of using the annual data from each calendar year, rainfall measures are computed using spring months from March to May, which represent the bulk of the growing season for the crops cultivated in the provinces surveyed by RUMiC-RHS (Meng and Yamauchi, 2015). The main analysis is replicated using different definitions of growing season, and falsification tests are run to check that there is no effect of weather shocks outside such growing season. In constructing county-specific measures of weather shock I compute the deviation of growing-season rainfalls in year t from their long-term average and normalise it by its county-specific standard deviation as follows:

$$Zscore\_Rain_{tk} = \frac{y_{tk}-\overline{y_k}^{78-10}}{SD_k^{78-10}(y)}.$$

The long term average is computed over a period of 33 years, from 1978 to 2010. Figure 3 shows the distribution of the *Zscore_Rain* for all county-year observations from year 2000 to 2010. Standardising the yearly rainfall deviation by the long term county–specific standard deviation allows to control for the fact that some counties might have very high rainfall standard deviations and thus are more likely in each period to experience large deviations from the average. Standardisation also provides a straightforward interpretation of the variable as Zscore_Rain = 1 (-1) corresponds to rainfalls 1 standard deviation above (below) the mean. I mainly focus on rainfalls (following Kleemens and Magruder, 2017) but I show that including temperature shocks does not affect the estimated impact of precipitation on labour allocation decisions.

3.2 Labour allocation across the farm, local off-farm and urban sector

Before moving to the empirical strategy I describe here some interesting patterns in the way individuals and households allocate labour across different sectors in rural China. From them it arises a picture of a pretty fluid labour market where households (as well as individuals) tend to diversify their supply of labour across different sectors.

Individual level. Descriptive statistics about individual labour supplies to different sectors are presented in Table 1. Statistics are calculated on the pooled estimating sample of 48,595 observations from year 2008, 2009 and 2010. Males represent about half of the sample, average age is 43, 84% of respondents are married and average education is 7.2 years. About 2 individuals out of 3 devote a positive amount of working days to the farm sector, confirming the importance of agriculture as the primary source of occupation. On the other hand, 28% of the sample supplies at least some working days to the local off-farm sector and 24% to the urban one (rural-urban migration). Participation shares sum up to more than 1 because many individuals tend to work in more than one sector during the same year. The unconditional average number of days per year supplied to the farm, local off-farm and urban sector are, respectively, 93, 60 and 65. While conditional on participation, the average number of days supplied to the three sectors is about 139, 214 and 270. In an average year, 42% of rural-urban migrants (i.e. individuals who have spent a positive number of days working in the urban sector) spend less than 300 days working in the city, and 18% spend less than 200 days.

Further, these numbers mask relevant heterogeneity along the age distribution in the amount of days of work spent in different sectors. Indeed, as Figure 4 shows, labour supply to the urban sector is highest for individuals aged 25-35 and declines with age, while supply to the farming sector increases with age and picks around age 55-65. Finally, labour supply to the local off-farm sector is highest for individuals aged between 30 and 50 and is lower for both younger and older ones. Although young individuals are more likely to engage in urban sector work while elderly ones are more likely to farm, there is a non-negligible positive probability of participating to each of the three sectors at any age between 16 and 65. Furthermore, it is not uncommon for individuals in our sample to engage in more than one sector during the same year. The first column in the panel B of Table 1 reports the share of individuals in each of the following 8 categories of labour allocation: 1) no work at all; 2) farm only; 3) local off-farm only; 4) urban sector only; 5) farm + off-farm sector; 6) farm + urban sector; 7) off-farm + urban sector; and 8) all three sectors. 95% of individuals engage in some form of work and almost half of them are dedicated only to farming, while 11% and 17% of individuals work in the local off-farm and in the urban sector only respectively. Yet, almost 1 person out of 4 diversifies his supply of labour across more than one sector during the same year. When people do so they tend to pair farming with either working in the local off-farm sector or in the urban one. It is indeed interesting to notice that almost 1 individual out of 3 of those who have been working in the urban sector have also supplied some positive amount of labour to one of the other two, in most of the cases the farming one.

The likelihood of individuals to spread their supply of labour across different sectors, and the extent to which they do so, varies across both the gender and the age dimension. Panel A of Figure

5 shows that although "farming only" is by far the most common choice for both females and males, males are double as likely than females to diversify their supply of labour across different sectors during the same year. Indeed 32% of males report to have been working in at least 2 sectors during the last year, while only 15% of females do so. As far as young (aged below 41) versus elderly (aged above 40) individuals, Panel B of the same Figure 5 shows that those aged above 40 are much more likely to engage in farming only while the shares of young and elderly individuals who participate to more than one sector are similar, respectively 22% and 25%.

Household level. I show descriptive statistics about household characteristics and their labour supply choices in Table 2. Household descriptive statistics are calculated on the pooled estimating sample of 11,382 observations from year 2008, 2009 and 2010. Average household size is 4 and the average number of members in the work force (aged 16-65) is 2.9. 86% of households in the sample engage in farm work, 47% in the local off-farm sector and 39% in the urban one. When we look at how households allocate their supply of labour across different sectors we observe that, despite the diffusion of off-farm and urban work, 1 out of 4 of rural households still engages in farming only. On the other hand, 61% of households diversify labour supply across more than one sector, 40% have someone who has spent some days working in the urban sector, and 12% are fully diversified, i.e. engage in all 3 sectors.

Labour supply variation over time. The descriptive statistics above show relevant cross-sectional variation in the likelihood of individuals and households to participate to different sectors and in the amount of working days supplied conditional on participation. This reveals how households tend to diversify the supply of labour across different sectors and away from farming to reduce, ex-ante, their exposure to income risk related to each one of the sectors.   Yet, what is of particular interest for this paper is how individuals change their labour supply allocation over time, in response to shocks in the relative productivity of sectors. Figure 6 shows the great amount of variation in the number of days dedicated to each one of the sectors within individuals over time. The figure plots the distribution of changes, within individuals and between consecutive years, in the number of days worked in each sector and in the total number of days worked. In each of the panels, the sample is restricted to individuals who reported positive days of work in the sector of interest in at least one year. As far as days of work in the urban sector are concerned, for only 30% of the observations there is no or little change (i.e. a change ranging between -/+10 days) between two consecutive years. Similar patterns are observable in the farm and in the off-farm sectors as well as in the total amount of days worked in a year. These statistics combine changes in the amount of days devoted to each sector deriving from variations along both the extensive and the intensive margin. In the empirical part I will analyze how such changes are, at least in part, an optimal response to weather shocks affecting agricultural productivity.

4. Empirical Strategy

The main threat to identification this study faces is the endogeneity of agricultural productivity shock. Farm productivity may indeed be correlated with unobservables that contribute to determine the supply of labour to off-farm and urban sectors as well. A household could, for instance, opt to invest less in pesticides and fertilizer because has decided to send a migrant away working in the city. In this case the estimates of the (negative) relationship between farm productivity and the probability to observe a rural-urban migrant in the household would be biased. To solve the endogeneity problem, I employ weather shocks as an instrument for agricultural productivity. As outlined above rainfalls have significant impact on farm productivity and income. At the same time, they cannot be affected by farmers' behaviour providing thus a fairly exogenous source of variation in agricultural productivity, which has been indeed widely used in the literature (see Rosenzweig and Wolpin, 2000, for an extensive literature review on the use of rainfalls as natural experiment). The key assumption for this approach is that, conditional on individual fixed effects and time fixed effect, local weather shocks are orthogonal to unobserved factors affecting individual labour allocation choices across the three sectors of analysis. Furthermore, crucially for identification, China's size and climatic heterogeneity generates variation in rainfalls both across counties within years and between years within counties. In the absence of detailed agricultural productivity data, I will identify a reduced form effect of weather shocks on labour reallocation rather than any structural parameter relating the latter to agricultural productivity. The empirical analysis looks at both individual level and household level labour allocation responses to weather shocks.

Individual level analysis. For the individual level analysis I estimate various versions of the following equation:

$$L^{l}_{ihkt} = \alpha_0 + \alpha_1 (Zscore\ Rain)_{kt} + Z'_{ihk}\xi + \gamma_i + \lambda_t + \varepsilon_{ihkt} \qquad \text{Eq. (1)}$$

where *i* indexes individuals, *h* households, *k* administrative counties, and *t* years. L_{ihkt} is either a binary variable indicating whether the individual participates in a sector or the number of days of work spent in a specific sector during the previous calendar year. On the one hand, when estimating the binary outcome equation (using a linear probability model) I study the participation decision to different sectors, i.e. the response to shocks through the extensive margin. On the other hand, when I estimate the days of work equation (unconditional on participation and using OLS) I am capturing a mixture of intensive and extensive margin response. There are three sectors: farm; local off-farm; and urban sector (to which I will often refer as rural-urban migration). Zscore_Rain is the county-specific rainfall shock defined above as precipitations during the growing season (March to May) at year t, measured in deviation from their long-term average and normalised by standard deviation. The estimates of the impact of rainfall shocks on labour supply allocation have to be interpreted as reduced form parameters of a two-step model where rainfalls affect agricultural productivity and individuals respond to the latter. Zscore_Rain is measured at the county level (there are 82 counties). I allow the error terms of individuals to be correlated across villages and over time, by clustering robust standard errors at the county level throughout the analysis. I also show that results also hold when computing standard errors that are robust to contemporaneous correlation across counties, within province-year. The vector *Z* includes some individual and household time varying characteristics such as marital status, number of family members respectively aged less than 16, in the work force and older than 65, and sex ratio of family members in working age. Finally, γ_i and λ_t are respectively individual and time fixed effects. I employ an individual fixed effects specification to condition on every time-invariant individual observable and unobservable characteristic - such as ability, preferences, productivity, migration costs etc. - that might affect labour supply decisions in the farm, off-farm and urban sector. This allows me to focus on changes in the labour supply across years within individuals which are determined by unexpected weather shocks, rather than on ex-ante labour supply strategies driven by, for instance, diversification purposes.

Household level analysis. In the household level analysis, I study how the allocation of household labour supply is shifted across sectors in response to weather shocks affecting agricultural productivity, both on the participation and on the intensive margin. To do so, I estimate various versions of the following equation:

$$L_{hkt}^{l} = \beta_0 + \beta_1 (Zscore\ Rain)_{kt} + Z_{hk}^{\prime}\xi + \delta_k + \mu_t + u_{hkt} \qquad \text{Eq. (2)}$$

where h indexes households, k administrative counties, and t years. L_{hkt} is either: a binary variable indicating whether the household participates in a sector; the number of days of work, per household member in the work force, allocated to each sector; and the share of total household working days devoted to them. Similarly to the individual case I use the binary outcome (estimating a linear probability model) to identify responses along the participation margin. Here as well I rely on the panel structure of the data and include household fixed effects (δ_k) to identify responses to weather shocks.

5. Results

5.1 Individual level analysis

Days of work. I start by exploring the average response to weather shocks. Table 3 reports OLS estimates of equation (1) above where the output is the number of days worked by the individual in different sectors (columns 1-3) and in total (column 4). Negative (positive) shocks of growing-season rainfalls are associated with less (more) farming and more (less) rural-urban migration. As we would expect, individuals tend to dedicate less time to farming when agricultural productivity is low, i.e. in presence of negative rainfall shocks, and to spend more time working in the city where wages and job opportunities are less affected by agricultural productivity. The elasticity of labour supplied to farming to weather shocks is slightly larger for women (Panel B, column 1 and 2). Yet, men tend to migrate more to the city than women during bad times (Panel B, column 5 and 6), even considering the difference in migration behaviour between the two genders at baseline. This result is probably due to women facing a higher fixed cost for rural-urban migration than males.

Estimates are both statistically significant and economically relevant. Days of farming decrease by 4.5% and days of work in the urban sector increase by 4.9% (5.7% and 3.6% respectively for men and women) on the baseline value in response to a mild negative weather shock, i.e. when rainfall realization is one standard deviation below the average. On average, in bad times, days of farming are substituted at a rate of 0.8 to 1 by days spent working in the city.

The coefficient in the local off-farm equation is positive but small in size and not statistically significant, indicating a very small, if any, average relationship between weather shocks and the labour supplied in the local off-farm sector. In fact, I will show later that such small coefficient masks interesting heterogeneity across age groups.

Regarding changes in total labour supply, men tend to shift their labour allocation across sectors leaving unchanged total labour supply. On the other hand, women, who are less engaged in the labour force to start with, tend to supply more work in years of high agricultural productivity. The estimates presented in this section capture a mix between the response along the participation margin (those shifting from zero days of work in a sector to some positive number and vice versa) and the intensive margin. We can imagine that, especially for sectors where entry costs are higher, such as local off-farm and rural-urban migration, differentiating between the response along the extensive and intensive margin might be relevant.

Participation. Table 4 presents estimates of a LPM of equation (2) where the output is an indicator as whether the individual supplies positive amount of days to different sectors. As far as farming is concerned, no significant response along the participation margin is detected when looking at men and women together (Panel A) suggesting that individuals are attached to the farming sector and tend to engage in it even when agricultural productivity is low. Only the coefficient for women (Panel B) is significantly different from zero although its magnitude is small. On the other hand, the probability to engage in rural-urban migration increases by 2.1% on the baseline value in response of a 1 standard deviation negative rainfall shock. This percentage effect is smaller than the one detected in the days of work equation (4.9%) suggesting that the increase in aggregate days of work in the urban sector steams from both the participation and the intensive margin, unless one assumes that the "new" rural-urban migrants spend on average many more days working in the city than the "old" ones. The response along the participation margin as far as rural-urban migration is concerned is striking different across genders. While the estimated effect of a 1 standard deviation negative rainfall shocks is equal to 2.6% on the baseline value for men, the coefficient for women is close to zero. These results confirm the possibility that fixed costs to participate to the urban sector (i.e. migration costs) are higher for women than for men and that the change in productivity in the farm sector vis-a-vis the urban one is not large enough to overcome fixed costs of moving. For this reason, women mainly respond through the intensive margin. Coefficients for the local off-farm equation are, although positive, not statistically different from zero.

My results are qualitatively in line with those by Jessoe et al (2016) for Mexico who find that unfavorable weather shocks (occurrence of high temperatures and low rainfalls) are associated with a decrease in local employment, in both agricultural and non-farm labour, and an increase in emigration. Results are also consistent with the evidence provided by Kleemans and Magruder (2017) for Indonesia, a country with climate and agriculture more similar to China, who find that precipitation z-score is negatively associated with internal migration.

Intensive margin. I now attempt to assess the relevance of individuals moving in and out of a sector compared to individuals always participating to it in determining the observed changes in labour allocation. To do so, I compare estimates obtained on the full "unconditional" sample (the one presented in Table 3) with those obtained when conditioning on participation, i.e. when only keeping, for each equation, individuals who supply some positive amount of labour to the relevant sector in each year when present in the survey. Results are presented respectively in Panel (A) and (B) of Table 5 and estimates for both the farm and the urban sector equation remain with the same sign when conditioning on participation. The coefficient in the farm equation when conditioning on participation is about 60% the size of the one in the unconditional regression, while in the rural-urban migration equation it is even slightly larger than the baseline one. In the local off-farm sector equation, the coefficient turns negative but is still statistically indistinguishable from zero.

These results, together with the larger effects found in the "days of work" compared to the "participation" regressions, suggest that an important share of the effect comes from changes in the amount of days devoted to sectors conditional on participation rather than from individuals moving in and out of such sectors. Focusing only on data based on participation would have caused to miss an important share of the action that is actually taking place in response to weather shocks. Indeed, the availability of data about the days of work supplied to each sector allows to detect responses to weather shocks that occur even without movements along the participation margin.

5.2 Robustness

In this section I test the robustness of the main estimates of the effect of weather shocks on labour supply reallocation measured in days of work. In the main analysis I calculate rainfall shocks during the agriculture growing season in the counties sampled by RUMiC-RHS, i.e. the months from March to May (Meng and Yamauchi, 2015). Here I test the robustness of results to an alternative definition of growing season, check whether rainfalls in months outside the growing season have any effect, and explore sensitivity to the inclusion of temperature shocks. Results are presented in Table 6 where panel (A) refers to farming and panel (B) to rural-urban migration, the first column reports the baseline estimates for comparison purposes.

Using a broader definition of growing season, which includes also one month before and one after the main one, does not alter the results. i.e. farming increases and rural-urban migration decreases with favorable weather shocks (column 2). Column 3 reports a falsification exercise where I test whether rainfall shocks measured outside the growing season have any effects on labour allocation. If the effect of weather fluctuations on labour allocation goes through agricultural productivity channel we would expect not to find any effect of such out-of-growing season shocks. Indeed (columns 3 and 4) coefficients of non-growing season rainfalls are very close to zero, plus its inclusion leaves virtually unchanged the main estimates. This occurs regardless of whether we use a more or less restrictive definition of non-growing season, respectively August-November and July-December.

Next, I test whether my estimates are sensitive to the inclusion of temperatures (measured in the same fashion as rainfall shocks, using growing season zscore) and it turns out they are not. Because temperature data are available only for a subset of county-years, column 5 presents estimates of Rain effect for the subsample for which temperature data is available when temperature is not included. Temperature is included in column 6 and, although it has positive (and significant) coefficient in the farm equation, the estimated effect of Rain on both farm and rural-urban migration remain virtually unchanged by its inclusion. Finally, in column 7, I show that allowing for contemporaneous correlation in the standard errors across counties within provinces does not particularly affect the significance of the main estimates.

Further, a share of individuals are not available for the entire period of analysis, but just for a subset of years (8,351 individuals). To test whether my results are sensitive to such attrition I estimate main days of work equations on the restricted sample of individuals not interested by the attrition, whose labour supply data is always available. Table 7 compares such estimates to those estimated out of the full sample. Reassuringly, estimates for all the four equations are very similar in size and significance level between the two samples.

5.3 Response heterogeneity

I now turn to study the heterogeneity of the response to shocks along the distribution of age. Figure 7 shows predicted coefficients (and 90% confidence intervals) in correspondence of a negative rainfall shock equal to 2 standard deviations for six different age groups. Coefficients where the outcome is days of work are presented in Panel (A) while those for the participation equations in Panel (B). Days of work in the farm sector decrease homogenously (estimates are all statistically significant at the 10% level) along the distribution of age from age 31 on. Because individuals aged <45 do less farming to start with (refer to Figure 4 for descriptive statistics about sectorial participation by age) for some of them a decrease in days of farming is translated into moving out of the sector (Panel B); while older individuals tend not to bring their farming days to zero. Labour supply to the urban sector increases in response to negative rainfall shocks for almost all age groups, and the likelihood to work in the city increases for 3 out 6 age groups. Estimates for younger individuals are larger (Panel A) but once the mean group-specific values of days of work in the urban sector are taken into account (engagement in rural-urban migration declines with age) individuals between 46 and 55 appear to be the most responsive group. As far as total working days are concerned, there is no clear pattern in the increase of total labour supply. Indeed, most of the adjustment seems to be coming from individuals reallocating time across sectors as opposed to increasing (decreasing) the total amount of labour supplied.

Results for the local off-farm sector reveal that the close to zero average effect found earlier was masking important heterogeneity across age groups. Estimates differ between young (< 45-50) and elderly individuals (>55), for both the days of work and the participation margins. Indeed, younger individuals tend to respond to negative shocks by reducing farming as well as participation to the local off-farm sector and increasing engagement in rural-urban migration. On the other hand, older individuals tend to farm less, although without leaving the farm sector completely. In fact, they tend to remain in the home village and increase participation into the local off-farm sector, while only marginally increasing rural-urban migration. Both young and elderly individuals respond to negative rainfall shocks by shifting labour supply away from farming, yet their next best alternative appears to be different. On the one hand, younger individuals, who face low migration costs and have relatively high productivity in urban sectors, tend to leave the home village and engage in rural-urban migration. They indeed seem to also exit the local off-farm sector - whose productivity is likely to be partially affected by rainfalls, although to a lower extent - in bad times. On the other hand, older individuals, who face high migration costs and low productivity in the urban sector, have their best alternative in taking a non-farming job within the rural home village, which might potentially include substituting in some family run business a younger family member who moved to the city. Finally, there is no clear pattern in the increase of total labour supply. Indeed, most of the adjustment seems to be coming from individuals reallocating time across sectors as opposed to increasing (decreasing) the total labour supply.

5.4 Household level analysis

I now turn to the analysis of labour allocation responses to weather shocks at the household level. Indeed, because some of the labour supply decisions might be taken at the level of the household, this part of the analysis also tests the sensitivity of the above results to a different decision-making framework. I aggregate individual labour supply data within families and in doing so I focus on individuals who have reported complete labour supply information for all the three years, in order to work with households whose composition is fixed over time. This leaves me with a balanced panel of 3,794 households. Table 7 shows that the sample of individuals used to construct the household level data is indeed similar to the full estimating sample employed for the individual level analysis.

Results for the days of work and participation analysis at the household level are presented in Table 8. Responses in terms of days of work per household members by sectors (columns 1-4) are similar to those estimated at the individual level, confirming the robustness of those findings. One difference is that a small increase in the total household supply of labour is detected. When I look at the share of total household days of work dedicated to different sectors as outcome (columns 5-7) I find that about 1% of total labour supply is shifted from farming toward rural-urban migration. That corresponds to a reduction of 2.1% with respect to the baseline share of household labour supply devoted to farming and an increase of 3.3% with respect to the baseline one devoted to working in the urban sector. The share of household labour supply to the local off-farm sector remains unaffected. This result might suggest that some within household re-allocation occurs as far as engagement in the off-farm sector is concerned and might be compatible with a story where young household members previously working in the local off-farm sector leave to work in the city in coincidence with a negative weather shock, while older members from the same households substitute them in the (perhaps family owned) off-farm activity. Finally, when I look at the likelihood of households to participate at all in different sectors, I find that the participation to the farm sector (and to the local off-farm) does not respond to weather shocks: some amount of farming is always performed even when agricultural productivity is low. On the other hand, the coefficient in the rural-urban migration equation has a negative sign corresponding to a 1% of the baseline value, but is not precisely estimated.

5.5 Land tenure insecurity, irrigation availability and labour reallocation

The analysis in this paper suggests that Chinese households do reallocate labour across sectors and away from farming when hit by negative agricultural productivity shocks. Yet, institutional features might have a role in easing or making more difficult the use of labour markets as an ex-post coping mechanism. One relevant institution is land property rights. Under China's constitution, rural land is the property of administrative villages, or collectives, but exclusive use rights are contracted out to individual households. Land can be reallocated within a village if necessary. Because the presence in the village and the active work of the land limits the likelihood that an household will face loss of land in a reallocation, heterogeneity in the use of administrative land reallocation across counties might influence the extent to which households are willing to shift away from agricultural work when hit by bad shocks. In the 2009 survey, households are asked to report whether in the village there has been a land reallocation in the last 5 years. I use the answer to this question as a proxy for the inclination of local administrative authorities to reallocate land in a specific village, and therefore for the likelihood that land reallocation will occur in the future. This assumption is based on the fact that, although reallocations depends on may factors, Giles and Mu (2014) identify some village characteristics - such as lineage group composition or demographic change - that in the cross section make some villages more incline to reallocate land. In other words, reallocation seems to be just more common in some villages than in others, thus I consider a past reallocation event as a proxy for the likelihood that reallocation will take place again in the future.

Formally, I interact the rainfall shock variable with my proxy for the risk that a reallocation will occur in the future in the specific village:

$$LABOUR^{l}_{ivkt} = \alpha_0 + \alpha_1(ZSCORE\ RAIN)_{kt} + \alpha_2(LOW\ RISK)_k + \alpha_3(ZSCORE\ RAIN * LOW\ RISK)_{vkt} + Z'_{ivk}\beta_1 + \gamma_i + \lambda_t + \varepsilon_{ivkt} \quad \text{Eq. (3)}$$

Where LOWRISK is an indicator variable for the low risk that a reallocation will take place in the future in the village. The parameter α_1 tells the response to weather shocks in villages characterised by high risk of reallocation and $\alpha_3 + \alpha_1$ provides the response for individuals in villages characterised by low risk of land reallocation[7]. Table 9 (column 1 and 2) reports estimates from individual level specifications employing individual fixed effects. I find that for individuals living in villages where the risk of land reallocation is high the elasticity of rural-urban migration to rainfall shocks is about 70% the size than the elasticity in low-reallocation risk villages, and it is not statistically different from zero. Although the potential endogeneity of the risk of reallocation does not allow to attach any causal interpretation, these results are consistent with a story where households living in villages where reallocations are more frequent are less incline to respond to shocks by shifting labour from the agricultural to other sectors and locations. Indeed, doing so would increase the likelihood of losing some land when a reallocation occurs. These findings also confirm results from Giles and Mu (2014) who find that the probability that a rural resident migrates out of the county declines by about 3 percentage points in response to an expected land reallocation in the following year. In this environment land tenure insecurity seems

[7] LOWRISK does not vary with time so α_2 cannot be identified.

to work as a constraint for households to freely reallocate labour across sectors to accommodate variations in sector-specific productivities.

Finally, I test the heterogeneity of the weather shock effects across another relevant household characteristic, irrigation status. Irrigation status is measured as the share of family land for which irrigation is available. I create an indicator for the share of irrigated family land is above the median value and implement a specification with interaction between rainfall shock and household irrigation status in year 2009 (the earliest year for which irrigation information is available) in the same spirit of eq. (3). I find that households whose share of irrigated family land at baseline is below the median value are more responsive to weather shocks (columns 3 and 4 of Table 9). In particular, the coefficients of Zscore Rain for households with relatively lower irrigation availability are about two times the size of those for households with higher irrigation availability. Such a pattern is very similar for both the farming and the rural-urban migration equation, suggesting that households with little irrigation are more exposed to weather fluctuations and more responsive to shocks. These last results provide further evidence that weather shocks affect labour allocation through their impact on agricultural productivity.

6. Concluding Remarks

This paper studies how individuals and households in rural China reallocate labour across sectors - away from farming and toward local off-farm and rural-urban migration - as a response to negative productivity shocks in agriculture. Understanding such responses is particularly relevant in light of the potential increase in frequency of extreme weather events that climate change is believed to be inducing.

I find that negative (positive) shocks of growing-season rainfalls are associated with less (more) farming and more (less) rural-urban migration. Thanks to detailed data on the number of days of work supplied to each activity during the past year, I am able to study the responses to weather shocks along both the participation and the intensive margin. I find that yearly working days devoted to farming drop by 4.5% while those spent working in the urban sector increase by 4.9% in correspondence to mild negative rainfall shocks, i.e. 1 standard deviation below the long term average. The increase in number of days individuals spend working in the city derives from both longer spells in the city for those already engaging in urban work (intensive margin) and from increase in the likelihood to participate at all in the urban sector (extensive margin), which increases by 2.1% on the baseline value. Next, I find interesting heterogeneous response across generations driven by age specific productivities in the urban sector and costs of leaving (even temporarily) the home village. While younger individuals tend to shift labour supply from farming toward working in the city, older individuals generally shift labour from farming toward local off-farm work, without leaving the home village. I also show that households with little irrigation seem to be more exposed to weather fluctuations and more responsive to shocks. Finally, I find that the elasticity of rural-urban migration to agricultural productivity in villages with high risk of land reallocation is about half the size of that in other villages. These results would suggest that increasing security of land property rights together with relaxing the current houku system of residence could increase efficiency of rural labour markets and allow households to better cope with adverse economic shocks.

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FIGURES

Figure 1 – Weather shocks and labour reallocation

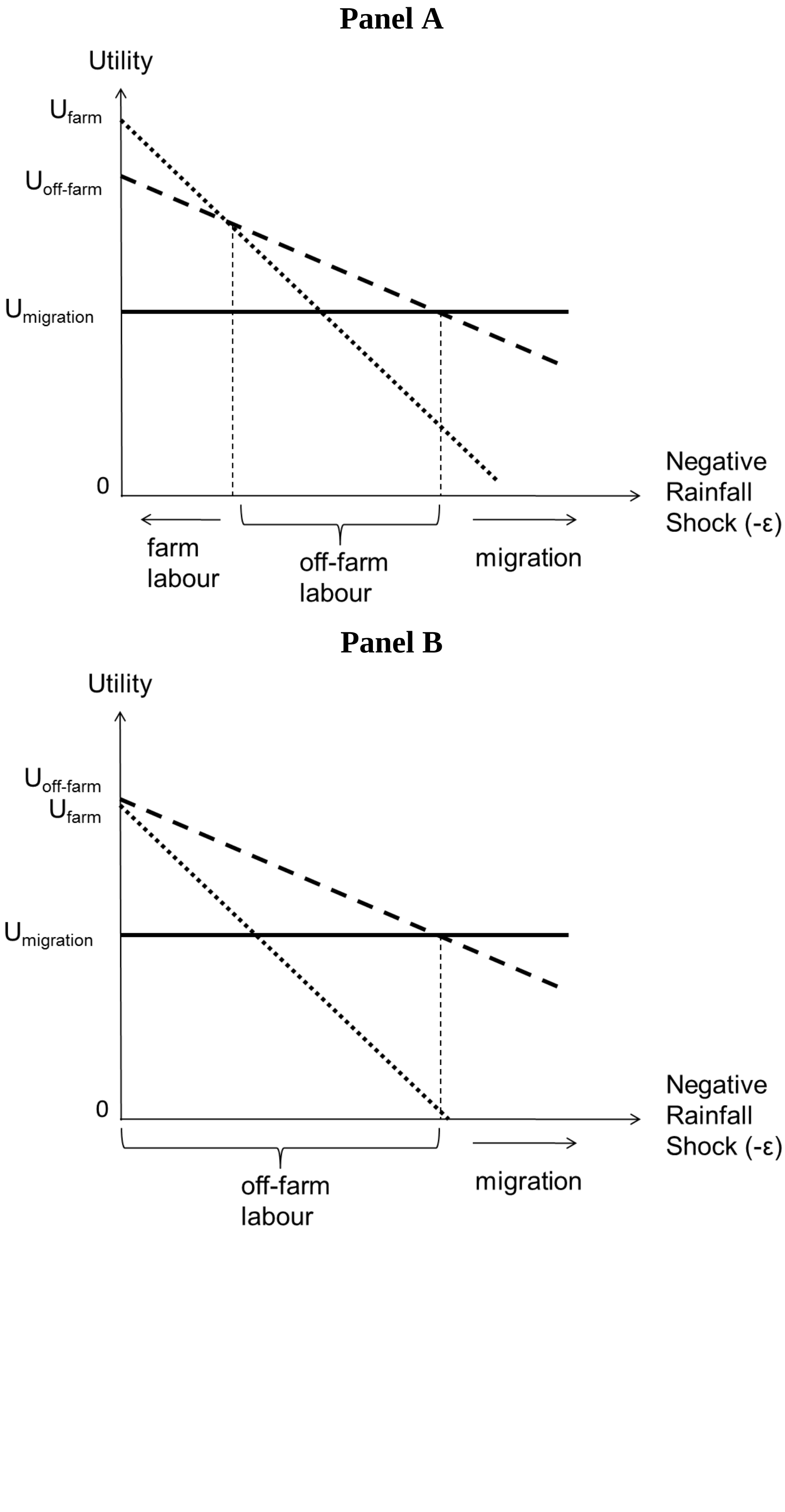
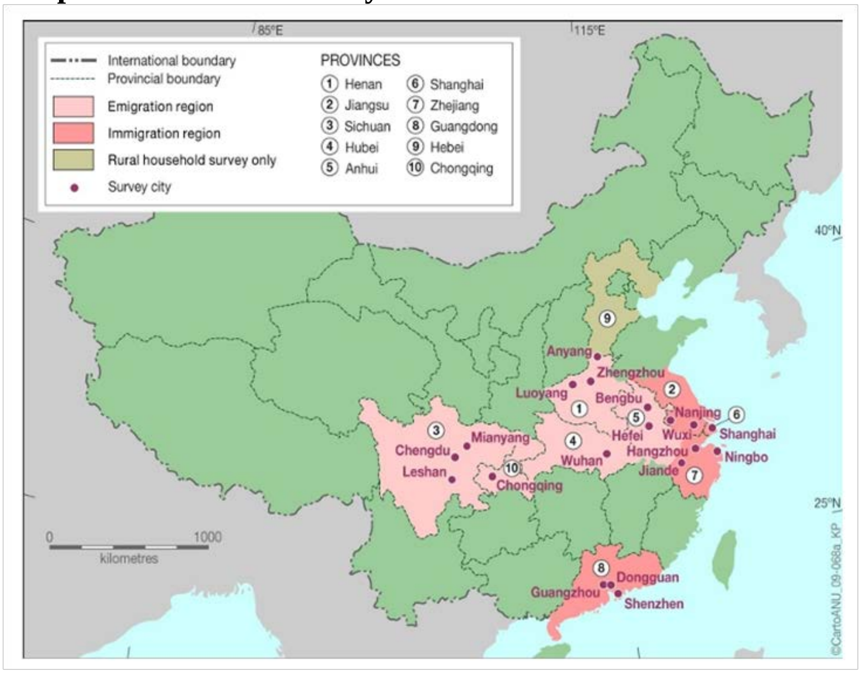
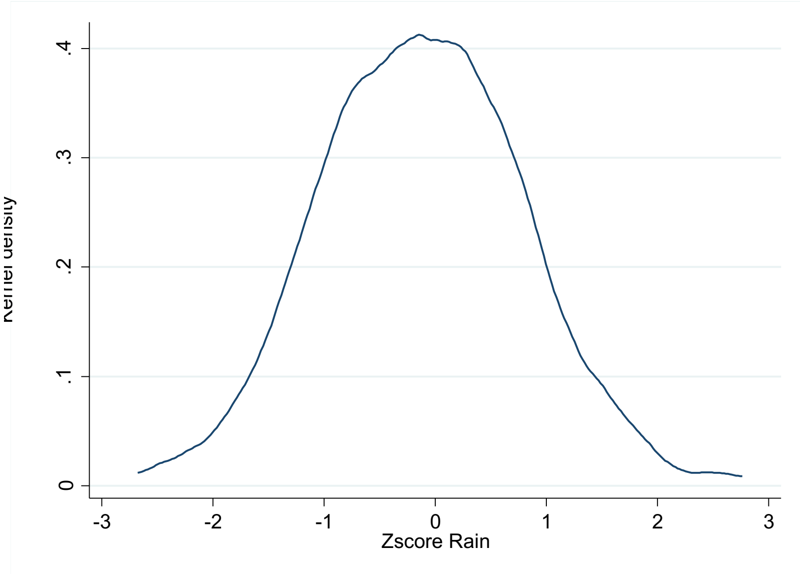


Figure 2 – Map of RUMiC-RHSurvey



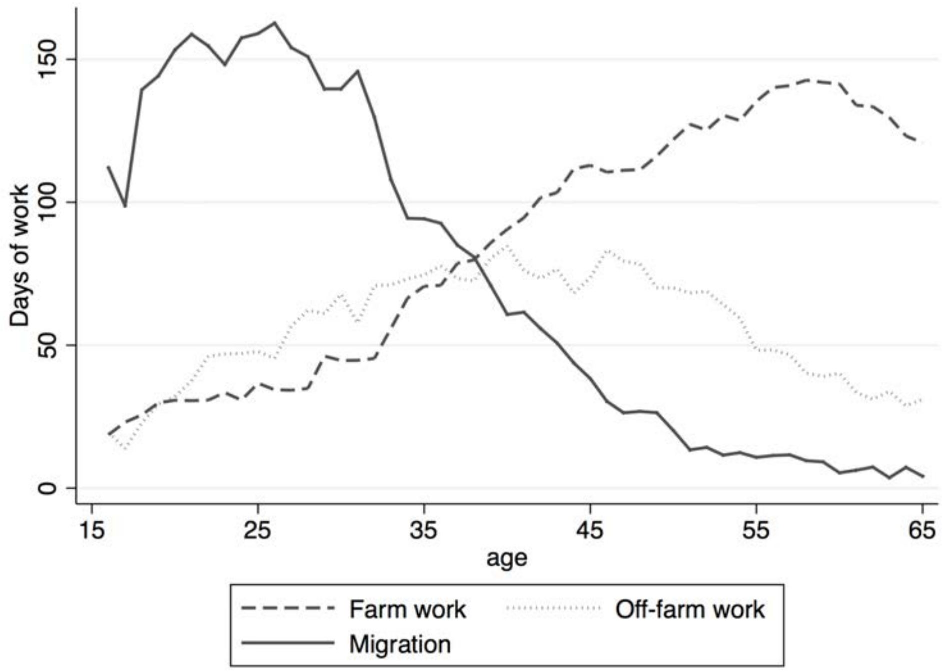
Note. The figure shows the provinces in which the RUMiC survey is conducted.

Figure 3 – Rainfall shocks distribution



Note. The figure shows the distribution of the main measure of rainfall shock (Zscore_Rain) for all county-year observations from 2000 to 2010. Zscore_Rain is a county-specific measure, given by the growing season (March to May) rainfall deviation from the county long-term average normalised by its standard: $Zscore\_Rain_{tk} = \frac{y_{tk} - \overline{y_k}^{78-10}}{SD_k^{78-10}(y)}$

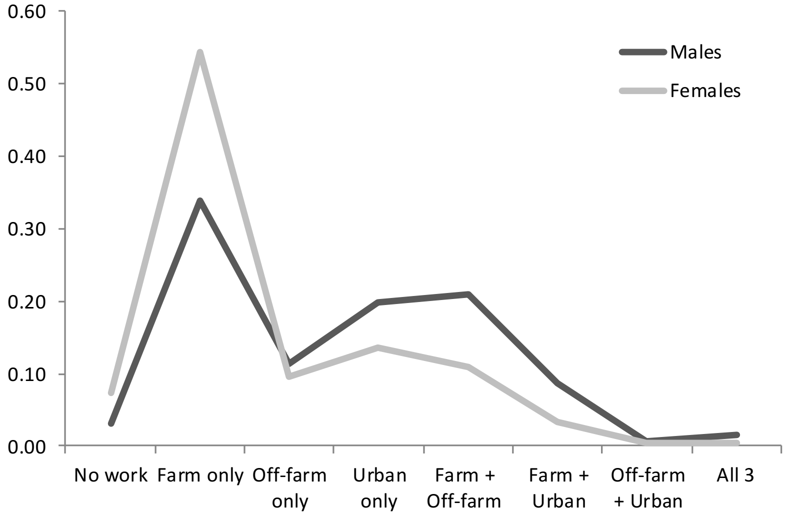
Figure 4 – Yearly days of work by sector and age



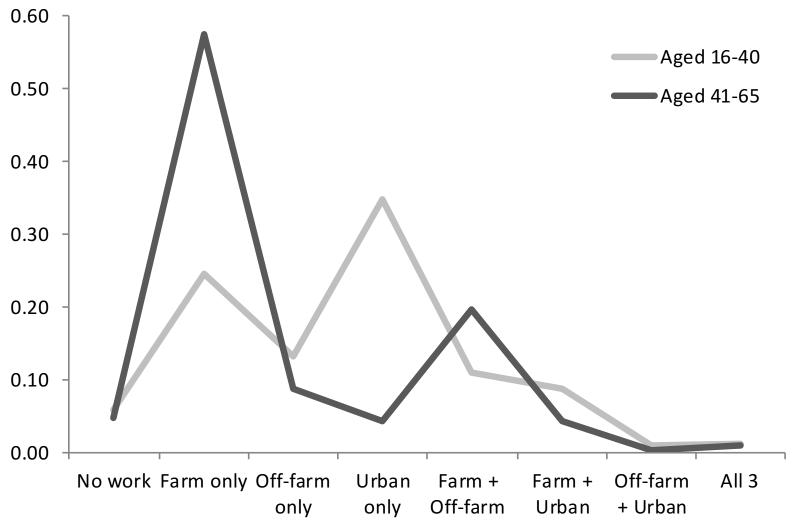
Note. The figure shows distributions of yearly days of work for each of the three sectors along the distribution of age. Pooled estimating sample: 48,595 individual-year observations from year 2008, 2009 and 2010.

Figure 5 – Share of individuals by sectoral participation

Panel (A): by gender

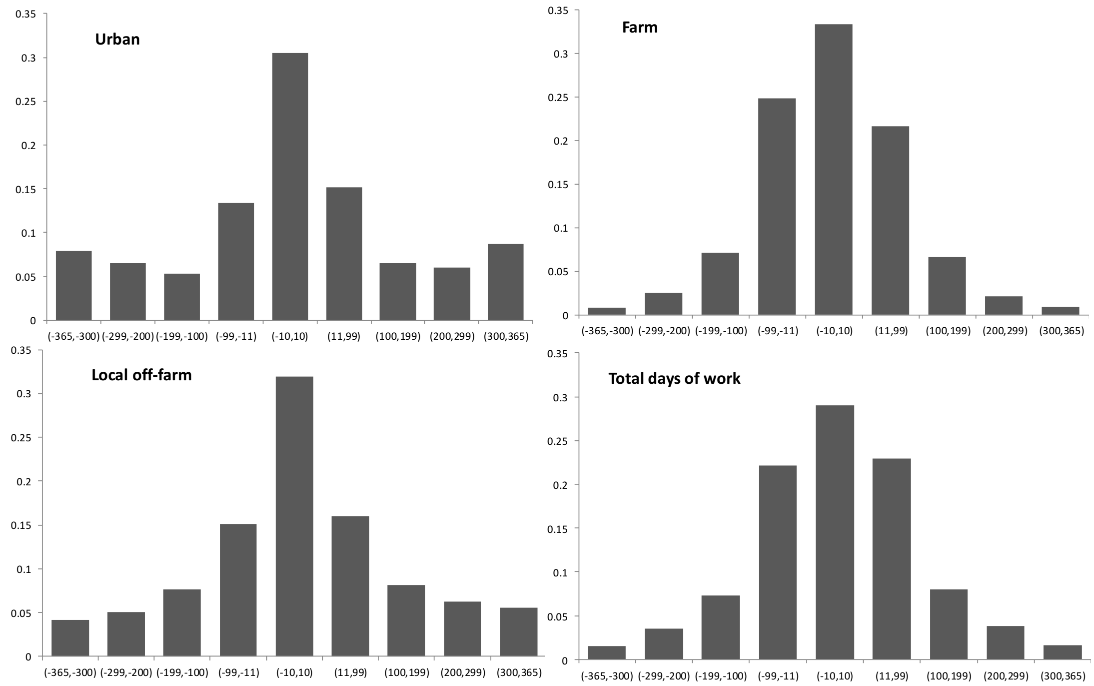


Panel (B): by age



Note. The figure shows the shares of individuals participating to different sectors and combination of them. Pooled estimating sample: 48,595 individual-year observations from year 2008, 2009 and 2010.

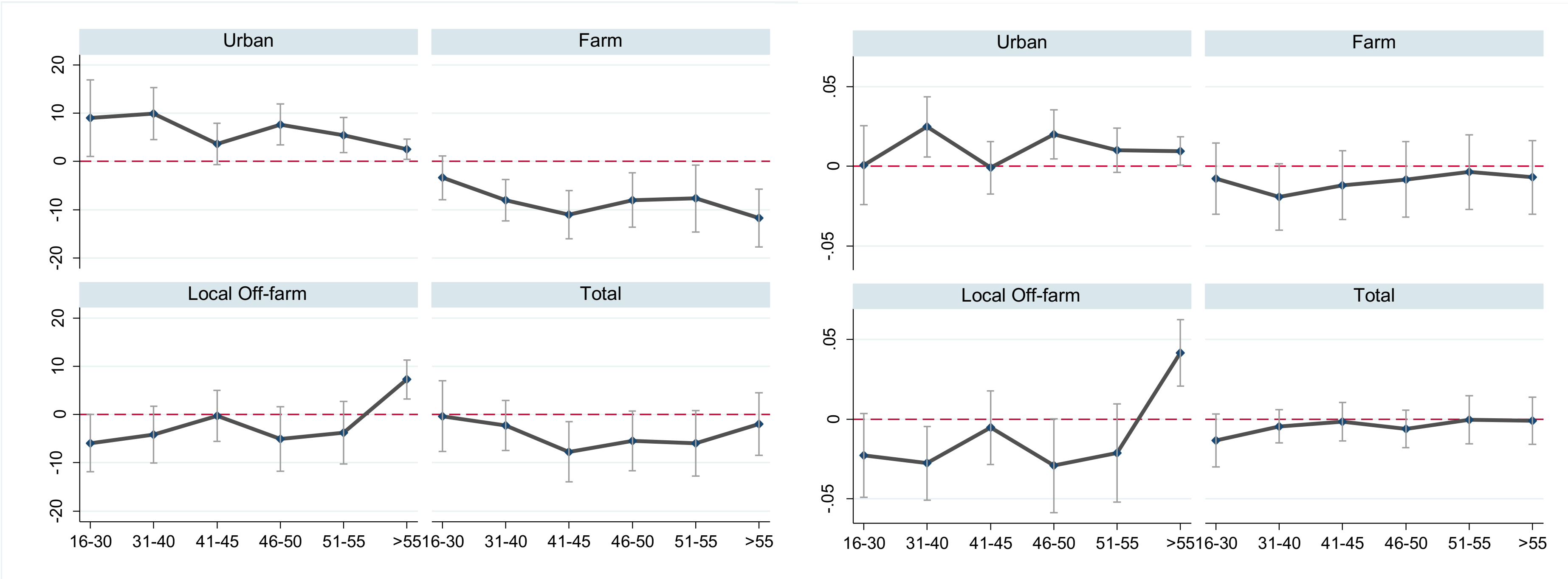
Figure 6 – Yearly changes in days of work supplied: by sector



Note. The figure shows distributions of within-individuals changes in the number of days of work supplied to each sector (and the sum of them) between two consecutive years. The sample includes, for each sector, individuals who supplied a positive number of days in that specific sector in at least one of the three years between 2008 and 2010. More precisely the number of individuals for each panel is as follow - Urban: N=5,948; Farm: N=13,800; Local Off-farm: N=7,302; Total days: N=17,847.

Figure 7 – Heterogeneous response to negative weather shocks: by age group

Panel (A): Days of work **Panel (B): Likelihood to participate**



Note. The figure reports predicted coefficients on Zscore_Rain (and 90% confidence intervals based on robust standard errors clustered at the county level) in correspondence of a negative rainfall shock equal to a 2 standard deviations, from regressions of outcomes on Zscore Rain and controls in an individual fixed effect specification, by age group. Individual and household time-varying controls include marital status, number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. In Panel (A) predicted coefficients derive from OLS regressions with days of work as outcome. In Panel (B) predicted coefficients derive from LPM regressions with an indicator for days of work >0 (participation).

TABLES

Table 1 Descriptive statistics: individuals

	Panel (A)			
	Mean	**Std. Dev.**	**Min**	**Max**
Male	0.51	0.50	0	1
Age	43	13	16	65
Married	0.84	0.37	0	1
Years of education	7.2	2.8	0	14
Participation by sector:				
Farm	0.67	0.47	0	1
Local Off-farm	0.28	0.45	0	1
Urban	0.24	0.43	0	1
Any	0.95	0.22	0	1
Days of work by sector:				
Farm	93	107	0	365
Local Off-farm	60	112	0	365
Urban	65	121	0	365
Any	218	110	0	365

	Panel (B)			
	Mean	**Number of days by sector:**		
Participation by sector:		**Farm**	**Off-farm**	**Urban**
No work	0.05			
Farm only	0.44	174		
Local Off-farm only	0.11		287	
Urban only	0.17			291
Farm + Local Off-farm	0.16	82	181	
Farm + Urban	0.06	50		225
Local Off-farm + Urban	0.00		96	176
All 3	0.01	67	78	116

Note. The sample includes all individuals aged between 16 and 65 and not currently in school or disabled who reported complete labour supply information in at least two of three years. Individual descriptives are based on an unbalanced panel of 18,9182 individuals resulting in 48,595 observations. Source: 2009, 2010 and 2011 RUMiC-RHS Survey.

Table 2 Descriptive statistics: households

	Panel (A) Mean	Std. Dev.	Min	Max
Household size	4.0	1.2	2	10
HH members in the work force	2.9	1.0	1	7
Participation by sector:				
Farm	0.86	0.35	0	1
Local Off-farm	0.47	0.50	0	1
Urban	0.39	0.49	0	1
Any	0.99	0.10	0	1
Days of work by sector (as				
Farm	0.47	0.38	0	1
Local Off-farm	0.29	0.38	0	1
Urban	0.24	0.33	0	1

	Panel (B) Mean	Fraction of total days of work: Farm	Off-farm	Urban
Participation by sector:				
No work	0.01			
Farm only	0.25	1.00		
Local Off-farm only	0.09		1.00	
Urban only	0.04			1.00
Farm + Local Off-farm	0.26	0.38	0.62	
Farm + Urban	0.22	0.37		0.63
Local Off-farm + Urban	0.01		0.52	0.48
All 3	0.12	0.27	0.28	0.45

Note. The sample includes all households with more than one individual in working age who reported full labour supply information in each of the three survey years, resulting in a balanced panel of 3,794 households (i.e. 11,382 observations).
Source: 2009, 2010 and 2011 RUMiC-RHS Survey.

Table 3 – Labour supply responses: days of work

Outcome - Yearly days of work:	Farm		Local Off-Farm		Urban		Any	
				Panel (A)				
	(1)		(2)		(3)		(4)	
Zscore Rain	4.15***		0.81		-3.20***		1.75	
	(1.15)		(1.10)		(0.87)		(1.30)	
In % of mean outcome	4.5%		1.4%		4.9%		0.8%	
Observations	48,595		48,595		48,595		48,595	
				Panel (B): by gender				
	Males	**Females**	**Males**	**Females**	**Males**	**Females**	**Males**	**Females**
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**
Zscore Rain	3.43***	4.88***	0.46	1.21	-4.65***	-1.70**	-0.76	4.39***
	(1.19)	(1.25)	(1.34)	(1.08)	(1.17)	(0.82)	(1.41)	(1.46)
Mean of outcome	89	98	73	47	81	47	243	192
Observations	24,942	23,653	24,942	23,653	24,942	23,653	24,942	23,653
Individual and HH contr.	X	X	X	X	X	X	X	X
Individual fixed effects	X	X	X	X	X	X	X	X

Note. The table reports OLS estimates from individual level regressions of the number of days devoted to working in different sectors on Zscore_Rain and controls, as well as individual fixed effects. Zscore Rain is the growing season rainfall deviation from the county long-term average normalised by its standard deviation. Individual and household time-varying controls include marital status, number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. In Panel B the same analysis is replicated separately for males and females. Robust standard errors are clustered at the county level (82 counties) and reported in brackets.
*** p<0.01, ** p<0.05, * p<0.01

Table 4 – Labour supply responses: participation

Outcome - Participation:	Farm		Local Off-Farm		Urban	
			Panel (A)			
	(1)		(2)		(3)	
Zscore Rain	0.005		0.004		-0.005*	
	(0.004)		(0.005)		(0.003)	
In % of mean outcome	0.7%		1.4%		2.1%	
Observations	48,595		48,595		48,595	
			Panel (B): by gender			
	Males	**Females**	**Males**	**Females**	**Males**	**Females**
	(1)	(2)	(3)	(4)	(5)	(6)
Zscore Rain	0.002	0.008*	0.004	0.005	-0.008**	-0.003
	(0.005)	(0.005)	(0.006)	(0.005)	(0.004)	(0.003)
Mean of outcome	0.65	0.69	0.34	0.21	0.31	0.18
Observations	24,942	23,653	24,942	23,653	24,942	23,653
Individual and HH contr.	X	X	X	X	X	X
Individual fixed effects	X	X	X	X	X	X

The table reports estimates from a linear probability model of an indicator for the individual working positive number of days in different sectors (participation) on Zscore_Rain and controls, as well as individual fixed effects. Zscore Rain is the growing season rainfall deviation from the county long-term average normalised by its standard deviation. Individual and household time-varying controls include marital status, number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. In Panel B the same analysis is replicated separately for males and females. Robust standard errors are clustered at the county level (82 counties) and reported in brackets. *** p<0.01, ** p<0.05, * p<0.01

Table 5 – Labour supply responses: days of work conditional on participation

Outcome - Yearly days of work:	Farm (1)	Off-Farm (2)	Urban (3)	Any (4)
	Panel (A): Unconditional (baseline)			
Zscore Rain	4.15***	0.81	-3.20***	1.75
	(1.15)	(1.10)	(0.87)	(1.30)
Observations	48,595	48,595	48,595	48,595
	Panel (B): Conditional on days>0			
Zscore Rain	2.55*	-0.76	-3.92**	0.67
	(1.52)	(1.77)	(1.70)	(1.16)
Observations	27,208	7,800	7,727	43,523
Individual and HH contr.	X	X	X	X
Individual fixed effects	X	X	X	X

Note. The table reports OLS estimates from regressions of the number of days devoted to working in different sectors on Zscore Rain and controls, as well as individual fixed effects. Zscore Rain is the growing season rainfall deviation from the county long-term average normalised by its standard deviation. Individual and household time-varying controls include marital status, number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. In Panel B, for each column, the sample is restricted to individuals who have supplied positive days of work in the relevant sector in every year. In order to allow the estimation of individual fixed effect, only individuals who have contributed to the sector a positive number of days for at least 2 years are included. Robust standard errors are clustered at the county level (82 counties) and reported in brackets. *** p<0.01, ** p<0.05, * p<0.01

Table 6 - Sensitivity to weather definitions

	Baseline definition of growing season: March-May	Alternative definition of growing season: Febr-June	Including non-growing season rainfalls: definition A (Aug-Nov)	Including non-growing season rainfalls: definition B (July-Dec)	Sample: temperature data available	Including temperature	SE robust to contemporaneous correlation within provinces
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
				Panel (A) - Farm (days of work)			
Growing season rain	4.15***	4.37***	4.09***	4.11***	5.18***	5.05***	4.15*
	(1.15)	(1.04)	(1.25)	(1.26)	(1.12)	(1.12)	(2.39)
Non-growing season rain			0.15	0.09			
			(1.10)	(1.10)			
Growing season temperature						4.61**	
						(2.00)	
				Panel (B): Rural-urban migration (days of work)			
Growing season rain	-3.20***	-1.88**	-3.30***	-3.30***	-2.57***	-2.63***	-3.20**
	(0.87)	(0.79)	(0.97)	(0.97)	(0.93)	(0.94)	(1.40)
Non-growing season rain			0.25	0.25			
			(1.01)	(0.99)			
Growing season temperature						1.92	
						(1.87)	
Observations	48,595	48,595	48,595	48,595	41,515	41,515	48,595
Individual and HH contr.	X	X	X	X	X	X	X
Individual fixed effects	X	X	X	X	X	X	X

Note. The table tests the sensitivity of estimated effects of rainfall shocks on farming and rural-urban migration (Panel A and B respectively) to various specification modifications. Column 1 reports the Vaseline estimates of the effect of Zscore Rain the growing season rainfall deviation from the county long-term average normalised by its standard deviation, where the growing season is considered to go from March to May. Column 2 uses a broader definition of growing season, from February to June. Column 3-4 includes as well rainfall deviations measured outside the growing season. Columns 5-6 tests the robustness of Zscore Rain estimates to the inclusion of temperature zscore (also calculated during the growing season). In column 7 standard errors robust to contemporaneous correlation across counties (within provinces) are employed. Individual and household time-varying controls are the usual. Robust standard errors are clustered at the county level (82 counties) and reported in brackets (except for column 7).
*** p<0.01, ** p<0.05, * p<0.01

Table 7 - Robustness of individual level estimates to attrition

	Farm	Off-Farm	Urban	Any
	(1)	**(2)**	**(3)**	**(4)**
		Panel (A) - Full sample		
Zscore Rain	4.15***	0.81	-3.20***	1.75
	(1.15)	(1.10)	(0.87)	(1.30)
Observations	48,595	48,595	48,595	48,595
		Panel (B) - Only individuals always available		
Zscore Rain	4.14***	0.47	-2.72***	1.89
	(1.28)	(1.22)	(0.89)	(1.42)
Observations	31,893	31,893	31,893	31,893
Individual and HH controls	X	X	X	X
Individual fixed effects	X	X	X	X

Note. The table tests the robustness of baseline estimates to the sample of individuals whose labour supply data are available for all 3 years. Panel (A) refers to the full sample, the one used throughout the paper while Panel (B) uses the sample of only individuals not affected by attrition and always present in the data. Individual and household time-varying controls are the usual. Robust standard errors are clustered at the county level (82 counties) and reported in brackets. *** p<0.01, ** p<0.05, * p<0.01

Table 8 – Household level labour supply responses

	Days of work by HH member				Share of total HH days of work			Participation		
	Farm	Off-Farm	Urban	Any	Farm	Off-Farm	Urban	Farm	Off-Farm	Urban
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Zscore Rain	4.45***	0.44	-2.44***	2.45*	0.010*	-0.002	-0.008**	0.002	0.003	-0.004
	(1.37)	(1.30)	(0.86)	(1.47)	(0.005)	(0.005)	(0.003)	(0.005)	(0.007)	(0.005)
In % of mean outcome	4.7%	0.6%	4.4%	1.1%	2.1%	0.7%	3.3%	0.2%	0.6%	1.0%
Observations	11,382	11,382	11,382	11,382	11,382	11,382	11,382	11,382	11,382	11,382
HH controls	X	X	X	X	X	X	X	X	X	X
HH fixed effects	X	X	X	X	X	X	X	X	X	X

Note. The table explores the effect of weather shocks on household labour supply. In columns 1-4 the outcome are days of work divided by the number of household members in the estimating sample; in columns 5-7 the outcome are the shares of total household days of work in different sectors; in columns 8-10 estimate derive from a LPM where the outcome are indicators of the household participating in different sectors. Zscore Rain is the growing season rainfall deviation from the county long-term average normalised by its standard deviation. Household time-varying controls include number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. Household fixed effects are included in all regressions. The sample includes all households with more than one individual in working age who reported full labour supply information in each of the three survey years, resulting in a balanced panel of 3,794 households (i.e. 11,382 observations). Robust standard errors are clustered at the county level (82 counties) and reported in brackets. *** p<0.01, ** p<0.05, * p<0.01

Table 9 – Land tenure insecurity and irrigation availability

Outcome: days of work	Farming (1)	Migration (2)	Farming (3)	Migration (4)
Zscore Rain * low land reallocation risk	3.69***	-3.05***		
	(1.33)	(0.99)		
Zscore Rain * high land reallocation risk	7.91***	-2.18		
	(2.44)	(2.31)		
Zscore Rain * irrigation below median			5.18***	-3.47***
			(1.62)	(1.16)
Zscore Rain * irrigation above median			2.75	-1.47
			(1.86)	(1.20)
Observations	40,051	40,051	39,104	39,104
Individual and HH contr.	X	X	X	X
Individual fixed effects	X	X	X	X

Note. In column 1-2 the table reports estimates for the effect of Zscore Rain on farming (column 1) and migration (column 2) for individuals living in villages with, respectively, low and high risk of land reallocation taking place. In columns 3-4 the table reports estimates for the effect of Zscore Rain on farming (column 3) and migration (column 4) for individuals living in households whose share of irrigated land is, respectively, below and above the median value. Individual and household time-varying controls include marital status, number of family members respectively aged less than 16, in the work force and older than 65, sex ratio of family members in working age. Robust standard errors are clustered at the county level (82 counties) and reported in brackets. *** p<0.01, ** p<0.05, * p<0.1.