WEATHER SHOCKS AND LABOR ALLOCATION: EVIDENCE FROM NORTHEASTERN BRAZIL[1]

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Abstract
This paper analyzes whether rural households use labor allocation to mitigate the effect of drought shocks in the Northeaster Brazilian context. We first document that water scarcity leads to lower income derived from farm work as main, and higher income from secondary jobs. We then examine the extent to which extreme droughts affect time labor allocation. Our results indicate that an additional drought shock per year is associated with greater likelihood of have more than one job, lower share of farm activities on the total hours worked, and higher share of secondary job. The effects are higher for poorer municipalities. These findings are consistent with a response to reduced agricultural profitability due to water scarcity and show the importance of non-agricultural activities as an autonomous mitigation mechanism.

Keywords: Drought shocks; rural households; labor allocation; Northeastern Brazil.

Resumo
Este artigo analisa se as famílias rurais usam a alocação de trabalho para mitigar o efeito de um choque de seca no Nordeste do Brasil. Primeiramente, fornecemos evidência de que a escassez de água está associada a uma menor renda derivada do trabalho principal, sendo este agrícola ou não, e positivamente relacionada a maior renda de empregos secundários. Em seguida, achamos que choques negativos de chuva estão fortemente correlacionados com as decisões de alocação de mão de obra. Um choque de seca a mais por ano está associado a maior probabilidade de ter mais de um emprego, menor participação do trabalho agrícola no total de horas trabalhadas e maior participação do trabalho secundário. Os efeitos são maiores para os municípios mais pobres. Esses resultados são consistentes com uma resposta de mitigação à rentabilidade agrícola reduzida devido à escassez de água.

Palavras-chave: Choques de seca; famílias rurais; alocação de trabalho; Nordeste do Brasil.

Classificação JEL: O13, O15, Q1, Q54

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1. Introduction

A consolidated body of research suggests that the incidence of extreme weather events, such as droughts and floods, will rise in the coming century as a result of increased global average temperature (Coates et al., 2014; IPCC, 2013). The economic costs of these climate-related extreme events may be substantial and far-reaching. Much of the discussion in literature has focused on the direct impacts of extreme weather events on health, agriculture, and income.[2] However, increasing attention is being paid to the mechanisms underlying these relationships. One intriguing question is whether families adopt loss-income mitigation strategies in response to extreme weather events. While previous studies provide strong evidence that droughts and floods can have an immediate effect on rural income, the extent to which families adjust labor supply to mitigate these effects has been very little investigated.[3] Documenting the quantitative importance of these labor supply and other behavioral household responses is crucial for guiding the targeting of policies intended to mitigate the adverse consequences of climate change.

Extreme weather events can have in particular important effects on time allocation of labor. In context where irrigation and genetically improved seed are unavailable, rainfall shocks are likely to negatively affect agricultural productivity, most notably causing lower yields of subsistence crops and reduce income from cash crops. As a result, engaging in agricultural activities become less attractive and household should rise the supply of non-agricultural work to hedge against declining agricultural profitability and consumption smoothing. Therefore, non-farm income plays a significant role in rural households by reducing income volatility.

Understanding the labor supply responses to weather shocks is particularly relevant in developing countries. Since these countries are located in areas that are warmer, they are expected to experience a disproportionate share of extreme weather events in the future due to climate change. Moreover, these countries have limited social safety nets and weak institutions, so households do not have access to the portfolio of adaptation strategies or avoidance behaviors often available in more developed countries.

This paper intends to show the importance of non-agricultural jobs as an autonomous mitigation mechanism. To do so, we provide empirical evidence on the relationship between rainfall shocks and household labor allocation in the Northeast Brazilian context. We believe that focus on Northeastern Brazil provides a compelling setting to investigate this question. First, it is the driest Brazilian region and it has long been subject to harsh climatic conditions, with recurrent events of drought and rising temperatures, leading to further enhance evaporation and reduce water availability (Ab'Sáber, 1999; Marengo, 2009). Second, one of the most populated semi-arid area of the world is localized in Brazilian Northeast, where more than 10 million inhabitants are located in rural areas. For a huge fraction of this population collecting water for consumption, hygiene, and agricultural production is a daily task that demands energy and resources. Lack of adequate access to water also increases the susceptibility to climatic shocks associated with fluctuations in rainfall (Ab'Sáber, 1999; Cirilo, 2008; Insa/MCTI, 2014; Rocha and Soares, 2015). Furthermore, half of all Brazilian rural

[2] See Barreca (2012), Barrios et al. (2008), Blakeslee and Fishman (2017), Deaton (1992), Deschênes and Greenstone (2007), Jayachandran (2006), Maccini and Yang (2009), Rocha and Soares (2015) and Zander et al. (2015).

[3] See Jessoe et al. (2017) and Rose (2001).

dwellers and family farming establishments are in Northeast. Almost all of the total area sown in the region is rainfed. Only 2 percent of net area is irrigated.[4] Therefore, we would expect rainfall to be an important driver of agricultural productivity and household income.

We make use of high frequency gridded information on precipitation and temperature to construct a municipality-by-year weather dataset which then is combined with household microdata by using place and survey month. Our identification strategy exploits variation in rainfall records over time within municipalities, and relies on the assumption that weather shocks, conditional on municipality and year fixed-effects, are not correlated with other latent determinants of labor supply. This identifying assumption is plausible insofar as households are unlikely to anticipate precisely a rainfall shock at a given moment in time and place.

We begin our analysis by providing evidence that negative rainfall shocks affect household income in our setting. Although income registries are likely to be subject to considerable measurement error in household surveys, we still observe that drought shocks are significantly associated with lower income derived from the main job. This is especially true when we consider income derived from agricultural activities. Moreover, higher incidence of drought shocks are significantly associated with increased income from secondary jobs, out of agriculture. These results give us confidence that rainfall shocks are in fact an income shifter in our setting.

We then explore the extent to which drought shocks affect labor time allocation. We find that negative rainfall shocks are associated with greater likelihood of being employed in more than one job, lower share of farm activities, and higher share of non-agriculture secondary job. We also assess whether these effects vary heterogeneously according with municipality's level of development. The results indicate stronger effects among families residing municipalities with lower per capita income. Taken in their entirety, these results are consistent with a mitigation response to reduced agricultural profits due to water scarcity.

A potential identification issue pervading our analysis is migration. What if families migrate away from areas affected by extreme droughts? Empirically this would be problematic only if families that migrate in response to a negative rainfall shock are different from those who do not. To explore this issue, we estimate the main regressions considering only families that live for at least five years in the current municipality. The results are broadly similar compared to our benchmark specification. In addition, when we explore whether rainfall shocks are associated with predetermined individual or household characteristics, we find no evidence that this happen. Thus, selective migration is unlikely to be a major problem. This is consistent with recent work in rural Pakistan that finds no effect of rainfall on the mobility of men or women (Mueller et al., 2014).

A small number of papers, focused mostly on reallocation of main job, have examined the relationship between weather and labor allocation. As part of a larger analysis, Jessoe et al. (2017) evaluate the effects of annual fluctuations in weather on employment in rural Mexico. They find no effect of rainfall or temperature shocks on agricultural sector, but show that non-agricultural labor decreases with increases in extreme temperature. Rose (2001) looks at rural Indian farm households to test labor supply responses to rainfall shock. She finds that the probability of participating in the labor market is significantly greater when unexpectedly low levels of precipitation are faced. To our knowledge, there has been no study of drought shocks on labor allocation

[4] These information are based on the Brazilian Agricultural Census 2006.

as mitigation strategy in Brazil. In this paper, we use more detailed information of the individual's work. We know the number of works the person is employed, whether the individual is employed in agricultural sector or not for each job, and the hours worked in both main and secondary job. The fact we know the hours worked supply and not just whether the person participates or not in the labor market, allow us to look at farm and non-farm work as complementary rather than as substitutes only.

We start in the next section with a little contextual information about Northeastern Brazil. In the third section we present our motivating model of the joint rural household decision regarding farm and non-farm labor supply. Section 4 describes our data and empirical strategy. Section 5 presents our benchmark results, and explores further empirical results. Section 6 concludes.

2. The Brazilian Northeast

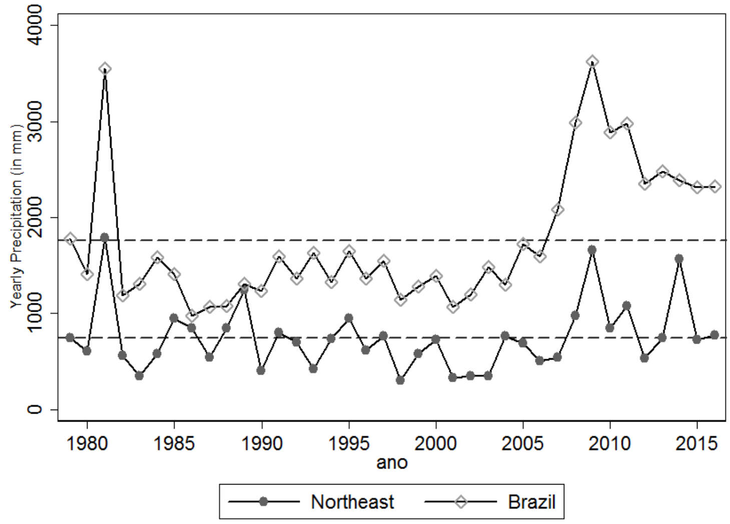
The Brazilian Northeast comprises nine states and 1,794 municipalities. This region is also the poorest and the driest Brazilian region and it has long been subject to harsh climatic conditions, with irregular annual precipitation, recurrent events of drought and rising temperatures. Furthermore, one of the most populated semi-arid area of the world is localized in Northeastern Brazil, where more than 23.5 million inhabitants are located, representing approximately 12% of the country's population (Ab’Sáber, 1999; Marengo, 2009). For a huge fraction of this population collecting water for consumption, hygiene, and agricultural production is a daily task that demands energy and resources. Lack of adequate access to water also increases the susceptibility to climatic shocks associated with fluctuations in rainfall (Ab’Sáber, 1999; Cirilo, 2008; Insa/MCTI, 2014; Rocha and Soares, 2015).

In Figure 1, we have yearly precipitation between 1979 and 2016 for the Northeast and for the rest of Brazil. Brazilian average historical precipitation is slightly above 1700 mm. In Northeast the average is quite below than what is observed for the rest of the country (749 mm). The figure illustrates that, in the 38-year interval portrayed, yearly precipitation in Northeastern Brazil did only reach the historical average for the rest of the country at a point in time, which was the year of 1981. The figure also shows the recurrence of rainfall deficits throughout the past decades.

The Northeastern Brazil is also the region with vast majority of the rural dwellers, more than 14 million inhabitants, which represents almost 50% of Brazilian rural population. The economy is largely based on extensive agriculture, 73% of rural dwellers have farm work as their principal employment. In this context, 89% of agricultural establishments are classified as family farms, employing more than 6 million people. The majority are small producers (with areas smaller than 10 ha) and occupy less than 5% of agricultural land. Also, almost all of the total area sown in the region is rainfed, with only 2 percent of irrigated net area.

In the context of Brazilian Northeast, where most of the farmers have no access to irrigation and genetically improved seed, rainfall shocks can disrupt agricultural production, most notably causing lower yields of subsistence crops and reduce income from cash crops. The limited access to credit or insurance markets and many internal and external constraints and stresses also could affect the farmers choice of mitigation strategies, and the labor market out off agriculture may be an alternative path to help rural households to hedge against declining agricultural profitability and consumption smoothing.

Figure1. Yearly precipitation in Northeastern Brazil and in the rest of the country



Notes: Author's calculation based on data from ERA-Interim, 1979-2016.

3. A model of rural household labor

We developed a simple model of the joint rural household decision regarding farm and non-farm labor supply. The household decides to allocate the time T among three activities: leisure (l^z), farm labor (l^{farm}) and non-farm labor (l^{off}), such that $T = l^z + l^{farm} + l^{off}$. Let c be consumption. The rural household utility function $U(c, l^z)$ is concave and twice differentiable. The total utility function of the rural household is

$$U(c, l^z) = u(c) + \alpha l^z \tag{1}$$

Let $\overline{w}$ denote the non-farm wage and, since the agricultural household is a price-taker in all markets (Singh, Squire and Strauss, 1986), we assume that $\overline{w}$ is determined exogenously. So, household will be paid $\overline{w}l^{off}$ for time spent working in non-farm labor. Let π be the revenue from agriculture, which is given by agricultural production. Agricultural production is determined by the amount of farm labor, weather shocks, and fixed capital and land. It may be represented by the production function $q(l^{farm}, R, \overline{K})$, where l^{farm} is the quantity of labor allocated to farm activities, R the weather shock, and $\overline{K}$ is capital and land.[5] R is a random variable that affects farm profits, a higher value of R indicates better weather. It could be defined as the deviation between the total rainfall in given moment of time and the historical average rainfall.[6] Literature shows that rural Northeastern Brazil turns positive rainfall shocks into unequivocally beneficial events, enabling us to assume that $\frac{\partial q}{\partial R} > 0$.[7] Total rural household income is given by the sum of farm revenue and non-farm income, and it may be represented by $I = Pq(l^{farm}, R, \overline{K}) + \overline{w}l^{off}$. Thus, consumption will be

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[5] In general, we assume that $\frac{\partial q}{\partial l^{farm}} > 0$, $\frac{\partial^2 q}{\partial l^{farm^2}} < 0$ and $\frac{\partial^2 q}{\partial l^{farm}\partial R} > 0$.

[6] Rainfall deviations below the historical average characterizes a negative shock, whereas deviations above the historical average settles a positive shock.

[7] See Rocha and Soares (2015).

$$c = I \tag{2}$$
$$c = Pq(l^{farm}, R, \overline{K}) + \overline{w}l^{off} \tag{3}$$

The time allocated to leisure is expressed by $l^z = T - l^{farm} - l^{off}$. Thus, we can substitute this into the maximization problem to get

$$\max_{l^{farm}\, l^{off}} U[Pq(l^{farm}, R, \overline{K}) + \overline{w}l^{off}, T - l^{farm} - l^{off}] \tag{4}$$

We consider the case where rural households allocate time for both farm and non-farm activities. In this case, the first order conditions of the optimization problem (4) are given by

$$u'(c)\left(P\frac{\partial q}{\partial l^{farm}}\right) - \propto = 0 \tag{5}$$
$$u'(c)\overline{w} - \propto = 0 \tag{6}$$

where $u'(c)$ is the marginal utility of the consume and $\propto$ is the marginal utility of leisure.

From conditions (5) and (6), one may verify that

$$\left(P\frac{\partial q}{\partial l^{farm}}\right) = \overline{w} \tag{7}$$

Condition (7) indicates that, on optimum, the farm wage is equal to the wage paid by non-farm activities. To ensure a globally concave objective function, and thus, a unique optimum, we assume that

$$\left[u''(c)\left(P\frac{\partial q}{\partial l^{farm}}\right)^2 + P\frac{\partial^2 q}{\partial l^{farm^2}}u'(c)\right]u''(c)\overline{w}^2 > \left[u''(c)\overline{w}\left(P\frac{\partial q}{\partial l^{farm}}\right)\right]^2 \tag{8}$$

We are interested in the effect that weather shocks have on the optimal level of both farm and non-farm labor. That is, how would we expect an adverse weather shock to affect the rural household labor decision? They would use non-farm labor as a mitigation strategy to weather shocks? These questions lead us to our two testable hypothesis:

- Proposition 1: Negative rainfall shocks decrease household farm labor supply.

Proof. From the first order condition:

$$\frac{\partial l^{farm}}{\partial R} \cong \overbrace{-\,u''(c)\overline{w}^2u'(c)P\frac{\partial^2 q}{\partial l^{farm}\partial R}}^{(+)} \tag{9}$$

Farm work has a positive relationship with R. In other words, an increase (reduction) in R implies in increasing (decreasing) farm labor. In this model, there is only one way that weather shocks affect the choice of farm work. When a drought is faced, the marginal productivity of agricultural labor will reduce, which implies a diminishing in the return of farm labor. Thereby, agricultural activities become less attractive. Household will allocate less time to farm labor, thus reducing l^{farm}. However, positive rainfall shocks increase the benefit to farm working, agricultural wage rises and household will increase farm labor supply

- Proposition 2: Negative rainfall shocks increase household non agricultural labor supply.

Proof. From the first order condition, we can derivate the effect of weather shocks on the optimal choice of non-farm working:

$$\frac{\partial l^{off}}{\partial R} \cong \overbrace{- u''(c)P\frac{\partial q}{\partial R}\bar{w}u'(c)P\frac{\partial^2 q}{\partial l^{farm^2}} + u''(c)\bar{w}^2u'(c)P\frac{\partial^2 q}{\partial l^{farm}\partial R}}^{(-)} \tag{10}$$

Weather shock has two effects on the optimal level of non-farm labor. First, a drought decreases both farmland productivity and the value of agricultural work, which affect the benefit of time spent in farm labor. Thus, non-farm labor becomes more attractive, and household will increase l^{off}. Second, droughts decreases the value of marginal productivity of farm labor. Since the marginal return associated to non-farm activities is higher, the household could choose non-farm labor above the optimal level, leading to rising the total income, and mitigating the shocks effect.

4. Data and Empirical Strategy

4.1. Household data

Our basic source for labor market outcomes in the rural Northeast is from the Brazilian Household Survey (PNAD). Every year since 1967, the Brazilian Bureau of Statistics (IBGE) has implemented the PNAD throughout Brazil during the month of September.[8] It is nationally and regionally representative, and contains detailed information on socio-economic and demographic characteristics. Since its implementation in 1967, PNAD passed through many methodological alterations along the years. Thus, we restrict our analysis to the period between 2001 and 2014, for which questionnaires and consistent sampling methodologies were maintained.

Importantly for our study, the PNAD asks whether respondents work with agriculture, are self-employed, wage-employee, employers, or whether they grow for their own consumption. In addition, respondents are asked to provide information about the number of jobs they have, and the amount of hours usually spent in each job per week. This allows us to calculate the participation of each job on the total of hours worked. The rural sample is comprised of 145,425 individuals from 40,519 households in 150 municipalities. Employment data are available for 92,006 individuals, among which 47,295 are the head of household.[9]

We restrict the sample to those living outside of urban areas because our causal factor of interest, rainfall, should mainly have an effect in rural areas. We also restrict

[8] Except in the Brazilian Censuses years, that is conducted of each ten years.

[9] The basic idea underlying our empirical approach is to compare householders who experienced different climatic conditions in a given moment in time. Using different rounds of the PNAD, we can compare families (individuals) in different moments in time and place, so that there is a great amount of variation across municipalities and years in weather conditions and our dependent variables. PNAD is not longitudinal, so we are unable to observe the same individuals in different years. However, this does not jeopardize our empirical approach. Our identifying assumption is that, conditional on municipality and year fixed effects, weather shocks are orthogonal to other determinants of the variables of interest. This plausible assumption is sufficient to estimate the impact of weather shocks on our labor outcomes. Thereby, the relevant source of variation in our study is at the municipality-level.

the sample to individuals aged 10 to 70. The householder's characteristics, just as gender, age, years of schooling, and family size, are also collected from the PNAD. Our main outcomes of interest include probability of have more than one job, ratio of farm work on the total worked, share of secondary job on the total of hours worked, and likelihood of at least one family member being employed in nonagricultural work (non-farm likelihood). Table 1 presents summary statistics of these variables.

Table 1. Summary statistics: rural Northeastern Brazil, 2001-2014.

	Mean	Std. deviation	Min	Max	Number of observations
Household characteristics:					
Gender	0.52	0.50	0	1	145,425
Age	33.90	18.37	10	70	145,425
Years of studies	4.81	3.62	1	17	145,425
Number of household members	4.46	2.08	1	17	145,425
Employment characteristics:					
More than one job	0.07	0.25	0	1	92,006
Farm work as main %	0.73	0.44	0	1	92,006
Share of farm job	70.43	44.38	0	100	92,006
Share of secondary job	2.82	11	0	97.82	92,006
Non-farm (likelihood)	0.42	0.49	0	1	92,006
Agriculture wage job	0.22	0.41	0	1	65,790
Agriculture self-employed	0.28	0.45	0	1	65,790
Agriculture employer	0.02	0.13	0	1	65,790
Agriculture unpaid	0.25	0.43	0	1	65,790
Agriculture own consumption	0.24	0.42	0	1	65,790
Non-farm wage job	0.63	0.48	0	1	26,216
Non-farm self-employed	0.27	0.44	0	1	26,216
Non-farm employer	0.01	0.12	0	1	26,216
Non-farm unpaid	0.05	0.23	0	1	26,216

Notes: This table shows summary statistics from PNAD database.

In rural Northeastern, more than 70% of individuals report agriculture as their principal economic activity. Most of them are self-employed, while 25% help another member of the household and do not receive any salary. On average, only seven percent of individuals are employed in more than one job (not shown in the table), and the share of time spent on these secondary occupations of the total hours worked is 2,82%.

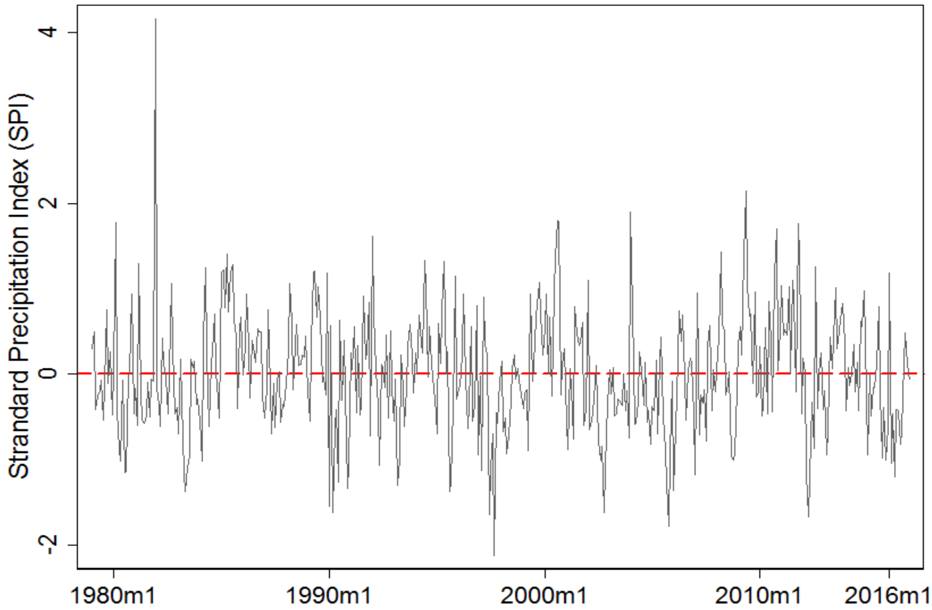
4.2. Climate data

Weather data are based on a reanalysis model, ERA-Interim. The ERA-Interim database provides daily temperature and precipitation information with horizontal and vertical resolution of 12 Km and covers the period from 1 January 1979 onwards. We use a geo-spatial software to aggregate the data to the municipality level and calculate an average of the points located inside the municipality limits.[10] We make use of this daily data in order to calculate summary measures and construct annual shocks.

[10] Considering the small grid used, almost all municipalities (1,485 of an total of 1,794) have had points inside their limits. For those that have had not, we use the four closest points on the grid to the center of the municipality, using the linear distances from the municipality's centroid to each node as weights.

To analyze the effect of weather on rural labor allocation, we construct several measures of drought shocks. Our first measure is the Standardized Precipitation Index (SPI).[11] The SPI calculation is based on the long-term precipitation record for a desired period. This long term-record is fitted to a probability distribution, which is then transformed into a normal distribution (Mckee et al., 1993). Its probabilistic nature gives it historical context, and since it is spatially consistent, it allows for comparisons between different locations, both are well suited for decision-making. Negatives SPI values indicate less than median precipitation and characterizes a drought. The drought intensity depends which value SPI reaches. Whether it reaches until -0.99 is within the "mild dryness" category, from -1 to -1.49 is "moderate dryness", if it is between -1.50 and -1.99 "severe dryness" and from -2 onwards is "extreme dryness" category. Any value above zero is not considered an negative rainfall event. Figure 2 presents the yearly averages for SPI.

Figure 2. Standard Precipitation Index (SPI) yearly average

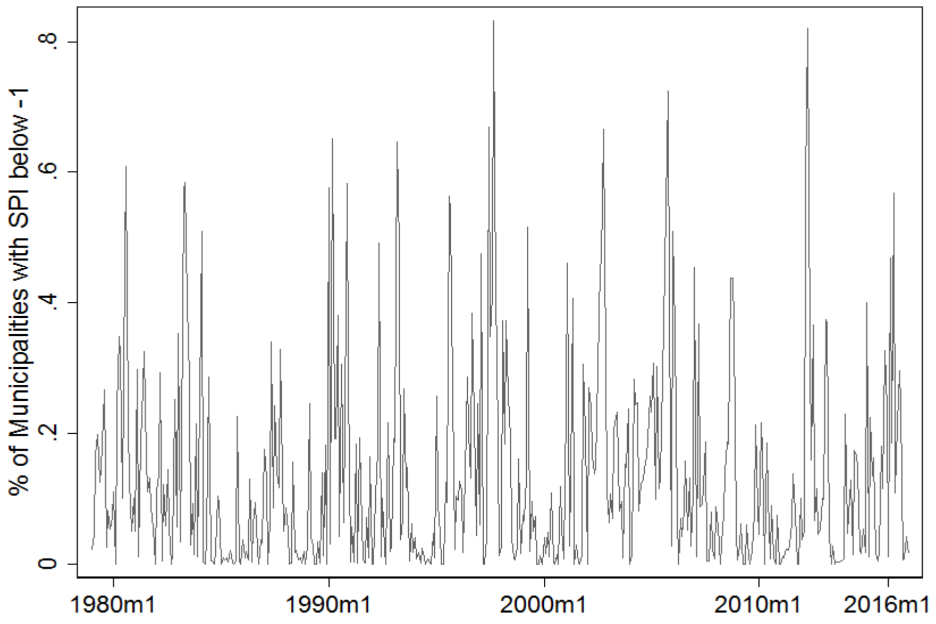


Notes: Municipality averages. Author's calculation based on data from ERA-Interim, 1979-2016.

To calculate the SPI index, we first aggregate weather data to the municipality-by-month-by-year level. These collapsed data contain total precipitation and average temperature for each municipality in a given month and year. We then define drought as equal to 1 if SPI is below -1 and 0 otherwise for a given month in each municipality. This definition is similar to the one employed by employed by Kaur (2013), Rocha and Soares (2015) and Shah and Steinberg (2017). Having defined a drought month, our final measure of exposure to droughts is computed as the number of months that each municipality faced a drought shock over the 12 months prior to PNAD survey month. Figure 3 reports the time series for the drought variable, indicating the percentage of municipalities with SPI below -1. One can see that there are periods with no municipality facing a drought, and others with drought heating 90 percent of the municipalities. This shows how the intensity of negative shocks varies geographically within a given month.

[11] See Mckee et al. (1993) for more details.

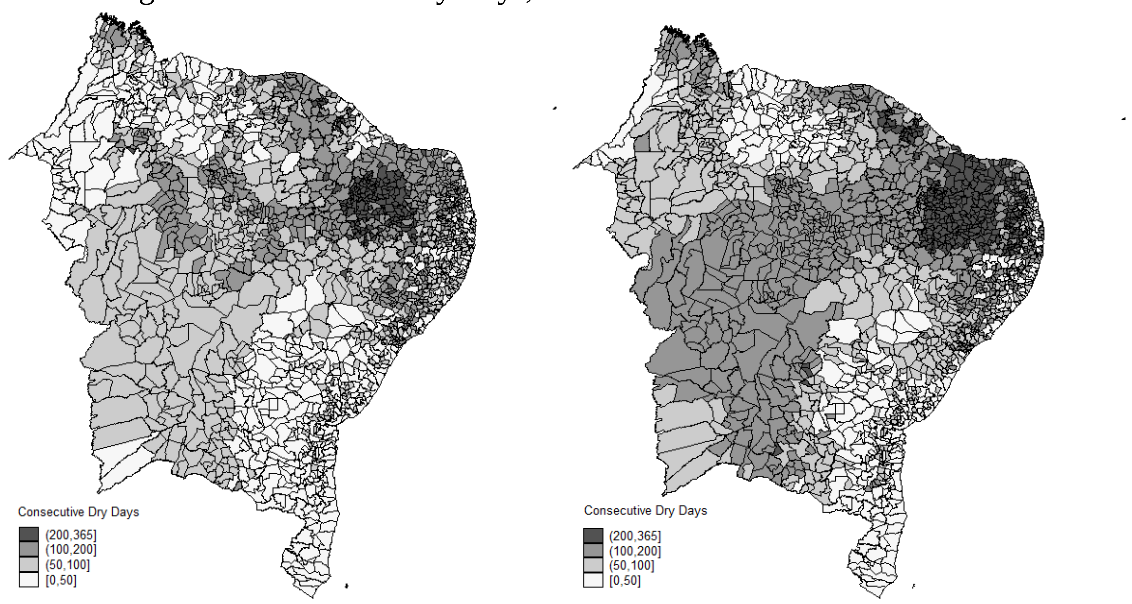
Figure 3. Drought (SPI) time series



Notes: Author's calculation based on data from ERA-Interim, 1979-2016.

Our second measure of drought shock is the longest consecutive dry days (CDD). Consecutive dry days is the greatest number of consecutive days for the period over the twelve months prior the survey, with daily precipitation amount below 1 mm. Figure 4 portrays the CDD in 1979 and 2016, respectively, for entire Northeastern Brazil. It shows that drought shocks at a point in time are not homogenous throughout the Northeastern region. Some areas may be suffering harsh rainfall conditions, spending more than three hundred days without rain, while others may not be.

Figure 4. Consecutive Dry Days, Northeastern Brazil - 1979 and 2016.



a) 1979 b) 2016

Source: ERA-Interim database.

4.3. Empirical strategy

To identify the impacts of weather shocks on rural household labor allocation, we estimate the following model:

$$H_{ijt} = \alpha + \beta_1 D_{jt} + \beta_2 X_i + \omega T_{jt} + \theta_j + \varphi_t + \varepsilon_{ijt} \quad (1)$$

where H_{ijt} is the labor outcome of interest for individual *i*, in municipality *j* and year *t*. The labor outcomes in this study are the number of jobs, ratio of farm work on the total worked and share of secondary job on the total of hours worked. We also consider these outcomes at the family level, since literature suggests that time allocation is as a household decision-making process rather than an individual one.[12] In particular, we consider a dummy indicating whether at least one household member is mainly employed in the non-farm market. D_{jt} is a drought shock measure (either the longest consecutive dry days in the 12 months prior to survey or the number of drought months in the same period) in year *t* and municipality *j*, which is our regressor of interest. We also control for householder's characteristics, just as gender, age, race and family size, by including the vector X_i. T_{jt} is the average temperature in the municipality *j*, on year t.[13]

The model includes municipality fixed effects (θ_j), which absorb any unobservable time invariant factors, including initial conditions and persistent municipality characteristics such as geography. Year fixed effects (φ_t) capture aggregate shocks impacting all Northeast region, including aggregated demand shocks, and regional policies and programs. Standard errors are clustered at the municipality level to account for serial correlation (Bertrand et al., 2004; Wooldridge, 2003).[14]

The parameter of interest β_1 measures the relationship between rainfall shocks and labor market outcomes. The identifying assumption underlying this statistical approach is that, conditional on municipality and year fixed effects, there are not determinants omitted of labor market outcomes correlated with the incidence of weather shocks. This seems plausible, given that the occurrence of extreme weather event at a given moment in time and place is unpredictable. Thus, our approach exploits arguably random fluctuations in rainfall from municipality-specific deviations in long-term rainfall after controlling for all seasonal factors and common shocks to all municipalities.

Although much of the variation in rainfall shocks over time within municipalities appears to be idiosyncratic, an identification issue could arise when following this specification. In particular, one may be concerned whether rural families respond migrating away from areas affected by extreme droughts. This would be problematic only if families that migrate in response to an extreme rainfall shock are different to families who do not. We address this issue in two way. First, we estimate the main regressions considering only families that live for at least five years in the current municipality. If regression results are similar to the ones derived from the baseline, we would be more confident that selective migration is unlikely to be a major issue. Second, we explore whether rainfall shocks are associated with predetermined

[12] See, for example, Démurger et al. (2010); Ellis (2000); Janvry and Sadoulet (2001); Jonasson and Helfand (2010); Mishra and Goodwin (1997); Vergara et al. (2004).

[13] We also control for bins of temperature in order to capture its nonlinear impacts. The results were the same, with temperature presenting no statistical significance.

[14] We also compute standard errors clustered at micro and macro-region level. Our results are robust to these standard errors.

individual or household characteristics. If different families are more likely to respond to rainfall shocks by migrating, one would expect to see significant effects of rainfall shocks on predetermined characteristics. As we shown below, there is very little evidence that this is the case. Perhaps, this is not very surprisingly, given we are exploiting temporary deviations in rainfall from the historical norm. Migration is likely to be a more salient issue in the case of prolonged and permanent changes in rainfall.

5. Results

5.1. Effects of Drought Shocks on Rural Labor Allocation

We begin by examining the effects of drought shocks on income. Table 2 presents the results from estimating equation (1) for the primary and secondary income. All regressions results are based on a specification that adjust for municipality fixed effects, year fixed effects, a set of demographic characteristics of the household head. Sample sizes and R-squared's of the regressions are shown at the bottom of the table.

Column (1) explores the effects of extreme negative rainfall shocks on income derived from the main job. The results indicate that negative rainfall shocks are significantly associated with lower income derived from the main job, especially for those engaged with farm activities (column 2). This is what one would expect given that a considerable fraction of population in this region depends on farming and related agricultural activities for living. The fact that we observe significant reductions in income associated to extreme droughts is reassuring given that data on income are generally measured with substantial error in household surveys.

Table 2: Effect of drought shocks on rural household income

	(1) Main Income (log)	(2) Main Income Agr. (log)	(3) Secondary Income (log)
Drought (SPI)	-0.0141 [0.0081]*	-0.0193 [0.0097]**	0.0251 [0.0119]**
Mean of dep. variable	5.4	5.17	0.46
Basic controls	Yes	Yes	Yes
Temperature control	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes
N	39720	21937	39720
R-sq	0.303	0.304	0.111

Notes: All outcomes are measured in log. Each coefficient is from a different regression. All regressions control for municipality and year fixed effects. We exclude observations in the top percentile of total income. Basic controls include gender, age, race and family size. Temperature control include the average temperature at municipality level. The number of observations differs in column (2) because it only considers households with agricultural job as main source of income. Robust standard errors (reported in brackets) are clustered at the municipality level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Column (3) investigates the effects on income derived from secondary jobs. The point estimate of the coefficient of interest is 0.0251 (standard error =0.0119), which statistically different from zero at the 5 percent level of significance. This estimate suggests that drought shocks are associated with higher income from secondary jobs.

An increase of one drought per year implies an increase of 5.45 percent in the dependent variable. We interpret this result as preliminary evidence that rural families respond to negative rainfall shocks by increasing the supply of secondary jobs. In particular, this evidence is consistent with a mitigation response to reduced income from cash crops due to water scarcity.

Having established that drought shocks affect rural household income, we turn to the analysis of labor supply responses. We present estimates of equation (1) for a series of labor outcomes in Table 3.[15] Panel A presents the results from using drought shocks based on Standardized Precipitation Index (SPI) as our key independent variable. Instead, Panel B considers the longest consecutive dry days (CDD) as the rainfall shock measure. The first three columns show results for outcomes measures for the head of household, while the last three consider labor allocation outcomes measures at household level, which assume that labor allocation is a collective decision rather than an individual one. We present results with sampling weights, which ensure that our final follow-up database is representative of the entire initial study population, although the results are very similar when ignoring sampling weights.

Panel A, column (1) shows that there is a positive and statistically significant relationship between drought and the number of jobs. One more drought shock per year increases by 5.63 percent the likelihood of being employed in more than one work. Column (2) looks at the share of farm job as main source of income on the total hours worked. The results suggest that there is a statistically significant negative effect of drought on the supply of farm work. The coefficient on ratio of agricultural activities on the total work is -0.567. Relative to mean of 69, this suggests an small decrease of 0.82 percent. But note that the estimate in column (3) implies an effect that is an increase of 6.6 percent in the share of hours worked in secondary job, relative to mean of 4.7. These results may indicate that they offer more hours to non-farm activities not trough a large decrease of farm labor supply but increasing the total amount of worked hours. This way they can compensate the loss of farm income, and mitigate the shock.

Columns (4) to (6) explore the effects of drought shocks on the outcomes measures at the family level. In columns (4) and (5), the results are qualitatively similar to the ones observed at the head of household level. In column (6) we find a statistically insignificant relationship between drought shocks and the likelihood of at least one family member chooses non-farm as main occupation. In addition, the estimated coefficient are very small in magnitude. For instance, the estimated coefficient of interest is -0.0004, which means that, one more drought month implies an effect that is 0,10% of the average and 0,0005% of the standard deviation in our dependent variable. In Panel B, we present analogous results using CDD as the independent variable. The qualitative patterns are similar – indicating in this case that droughts shocks are associated with rural households labor allocation – though the quantitative patterns are smaller. This difference might be due to rainfall characteristic, not normally distributed, and to the fact that SPI take this in account. Couttenier and Soubeyran (2013) have argued that several alternative measures of water stress are more efficient than the linear rainfall measure, and the SPI is one version of these measures. In light of the results from Table 3, we concentrate from now on on the sum of drought months based on SPI as our preferred independent variable.

[15] We also estimate regressions with the Terrestrial Air Temperature and Terrestrial Precipitation: 1900–2010 Gridded Monthly Time Series data base. The results are similar to ones find with ERA-Interim data base. Results available upon request, not shown here due to space limitation.

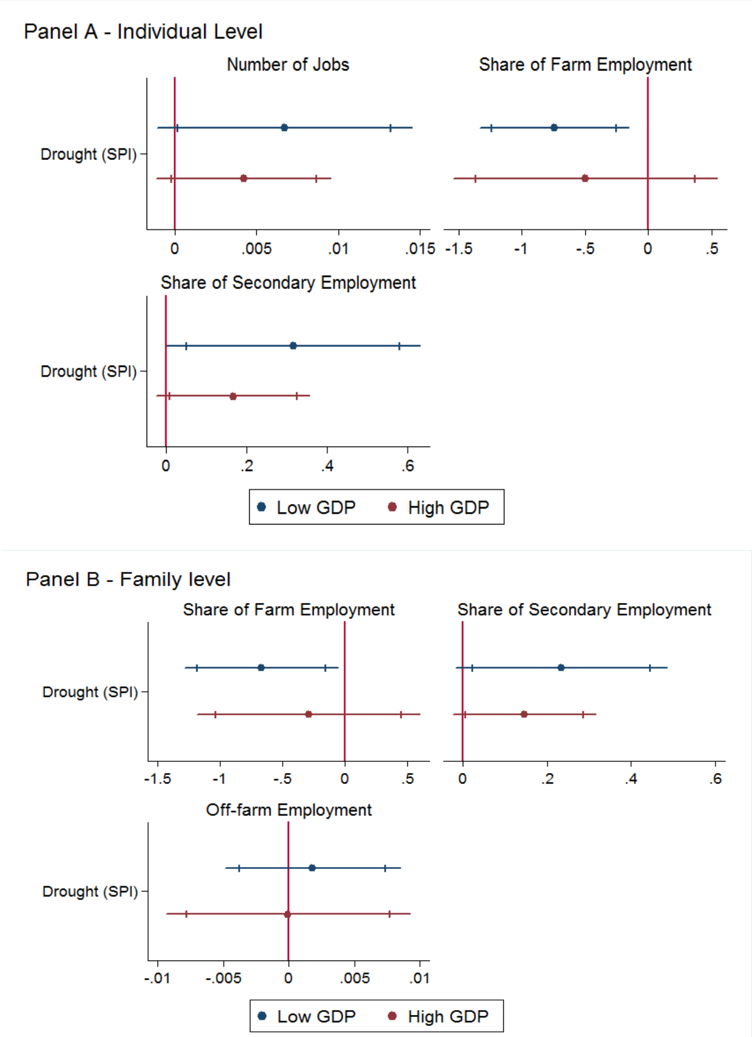
Table 3: Effect of drought shocks on rural household labor outcomes

	(1) Number of Jobs	(2) Share of farm employement	(3) Share of secondary employment	(4) Share of household farm employment	(5) Share of household secondary employment	(6) Non-farm employment
Panel A						
Drought (SPI)	0.0062	-0.5673	0.284	-0.4492	0.2152	-0.0004
	[0.0031]*	[0.2570]**	[0.1248]**	[0.2709]*	[0.0990]**	[0.0029]
Panel B						
CDD	0.0003	-0.0267	0.01	-0.0291	0.009	0.0002
	[0.0001]*	[0.0179]	[0.0057]*	[0.0184]	[0.0046]*	[0.0002]
Mean of dep. var.	0.11	69.5	4.37	65.9	3.47	0.37
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Temperature controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	40006	40006	40006	42952	42952	47295
R-sq	0.129	0.177	0.121	0.182	0.122	0.116

Notes: Each coefficient is from a different regression. Each panel corresponds to a different independent variable. All regressions control for municipality and year fixed effects. Columns (1) to (3) measure the outcomes at the head of household level, while in columns (4) to (6) the outcomes are at the household level. Each dependent variable in columns (2) to (5) refers to the share of the mentioned work on the total of hours worked. Basic controls include gender, age, race and family size. Temperature control include the average temperature at municipality level. Robust standard errors (reported in brackets) are clustered at the municipality level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To assess potential heterogeneities of the effects of negative rainfall shocks we stratify the sample according to level of municipality GDP per capita. Exploring GDP is of special interest since it is a reasonable proxy for local development. It seems to reasonable to expect smaller impacts of extreme droughts on income and thus on time labor allocation in more developed areas where there are often higher access to credit markets, more formal social safety net programs, and where the capacity of adaptation is higher. Figure 4 portrays the coefficients, 90 and 95 percent confidence intervals from estimating equation (1) for both municipalities with low and high GDP per capita separately. If the municipality is characterized by GDP per capita at the 50th percentile of the Northeast GDP distribution it is considered a low GDP municipality, otherwise it is a high GDP one.

Figure 4. Effects of drought shocks on labor outcomes by GDP per capita level



Notes: This is an event-study created by regressing labor outcomes on drought shocks and on a set of controls. The controls include municipality and year fixed effects, individual and household characteristics such as gender, age, race and family size. Temperature control include the average temperature at municipality level. Robust standard errors (reported in brackets) are clustered at the municipality level.

In Panel A, we regress labor outcomes of the head of household on drought shocks. One can see how the effect of negative rainfall shocks changes with income per capita. Lower income seems to be associated with higher impacts of rainfall variation. When we compare the likelihood of being employed in more than one work, one can observe a positive significant effect of drought shocks in municipalities with low GDP per capita and a statistically insignificant effect in those with high GDP. Individuals faced a drought shock in the previous year are 0.67 percentage point more likely to report having more than one job in the survey month, this is an increase of 5.58 percent from a mean of 0.12. While one more drought shock is not statistically significant to impact the share of farm work in high GDP municipalities, for those whom live with low income the point estimate of the coefficient of interest is -0.74 (standard error =0.29), which statistically different from zero at the 5 percent level of significance. The effect is larger in the share of secondary employment, increasing 7.5 per cent relative to a mean of 4.82. Panel B plots our baseline model for dependent variables at the family level. The qualitative and quantitative patterns are similar to ones find in Panel A. The results show that individuals with lower income are more vulnerable to weather shocks, and confirm the importance of adjustments in labor allocation to protect income due to decreasing in agricultural productivity.

The Northeastern presents vast variation in precipitation within year and between municipalities. One might expect there to be significant heterogeneity according to prevailing rainfall patterns. So we asses if drought shocks will have the same impacts on labor outcomes where rainfall levels are bellow 50th percentile of historical average (low rainfall patterns) as they would in areas that are above the median (high rainfall patterns). In Table 4, we regress labor outcomes on weather shock, as well as their interaction with a dummy indicating whether the municipality is low or high rainfall pattern. The interaction term indicates whether the effect of the drought shock depends on more general climate conditions. This is similar to the strategy employed in (Blakeslee and Fishman, 2014). The drought variable shows similar coefficients to those found before, and the drought shock interaction term are small and not significant. Thus, there is no evidence that the effect of negative rainfall shocks is mitigated by higher median rainfall levels.

Table 4. Effect of drought shocks on rural household labor outcomes by rainfall level

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of Jobs	Share of farm employement	Share of secondary employment	Share of household farm employment	Share of household secondary employment	Non-farm employment
Drought (SPI)	0.0075	-0.546	0.3448	-0.5214	0.2698	-0.0004
	[0.0038]**	[0.3033]*	[0.1536]**	[0.3263]	[0.1276]**	[0.0033]
Drought x low rainfall	-0.003	-0.0465	-0.1331	0.1569	-0.1185	-0.0001
	[0.0031]	[0.2889]	[0.1353]	[0.3074]	[0.1025]	[0.0031]
Mean of dep. var.	0.11	69.5	4.37	65.9	3.47	0.37
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Temperature controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
N	40006	40006	40006	42952	42952	47295
R-sq	0.129	0.177	0.121	0.182	0.122	0.116

Notes: Each coefficient is from a different regression. All regressions control for municipality and year fixed effects. Columns (1) to (3) measure the outcomes at the head of household level, while in columns (4) to (6) the outcomes are at the household level. Each dependent variable in columns (2) to (5) refers to the share of the mentioned work on the total of hours worked. Basic controls include gender, age, race and family size. Temperature control include the average temperature at municipality level. Robust standard errors (reported in brackets) are clustered at the municipality level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

5.2. Alternative rainfall measures

Considering the agricultural channel for the observed drought effects on labor allocation, we test if those shocks occurring during the pivotal monsoon season are more relevant in order to determine farmers job allocation response. To do this, we disaggregate our annual measure of drought shock into a specific period within the agricultural season and evaluate the impact of this shock on labor allocation. The period considered is the rainy season of current year *t* (February-April), which impact the production of the crops that are planted around December of year t-1 and January of year t.[16] In Appendix, table A1 reports the estimated impacts of monsoon drought shocks on labor outcomes. The results show that negative rainfall shocks during the rainy period reduce agricultural labor by 5.45 percent for the head of household and also increase by 34 percent his share on non-farm activities, relative to mean of 4.7. For family level, the results are pretty much the same, however, we do not find that the share of household farm employment is statistically sensitive to monsoon season shocks. Perhaps this happens because farmers may be compensating for a negative shock by increasing family labor and decreasing hired labor.

We also investigate if the consecutive occurrence of negative rainfall shocks has substantial impact on labor outcomes. We compute the longest consecutive number of months that each municipality faced a drought shock over the 12 months prior to PNAD survey month. Then, we create a dummy equal to one if the municipality faces two or more consecutive drought shocks and equal to zero otherwise. In appendix table A2, we follow our baseline model and regress labor outcomes on 2-or more consecutive drought shocks. The estimates reported in table A2 show that consecutive drought shocks have a significant effect on probability of being employed in more than one job (20 percent increase, relative to mean of the dependent variable). The impact is also statistically significant on the share of farm employment on the total of hours worked for the head of the family. The coefficient is -1.737, which relative to mean of 69, suggests a decrease of 2.49 percent on the ratio of agricultural activities. In column (3), the results show that consecutive drought shocks lead to a meaningful increase on hours spend at non-agricultural work (20 percent relative to its mean). The effect is similar to the outcomes at household level, for both variables (columns (4) and (5)).

One might expect that consecutive dry months have greater impact on labor outcomes than isolated drought shocks during the year. To verify this assumption, we compare the magnitude of the coefficients on the drought indicator in table 3, with the coefficients in appendix table A2. We find that a standard deviation increase in the number of drought months increases the likelihood of the head of household has more than one work by 8.5 percentage points. Whereas a standard deviation increase in two or more consecutive drought shocks enhances the probability of being employed in more than one job by 8.9. For one standard deviation in the number of drought months, the rate of farm work declines by 1.2 percentage points and the share of non-agricultural activities increases by 9.8 percentage points. When we look at a standard deviation increase in two or more consecutive dry months the values are basically the same (decrease of 1.1 percentage points on farm work and a raise of 9.2 percentage points on non-agricultural job). The magnitude is also similar when comparing the coefficients at family level.

5.3. Further Results

As mentioned before, we expect that much of the variation in rainfall shocks over time within municipalities is idiosyncratic, but an identification issue could arise whether rural families respond to rainfall shocks by migrating away from areas affected by extreme droughts. We assess on this issue in two way. First, in Appendix table A3 we replicate the baseline specification using only the rural households that live for at least five years in the current municipality. As can be seen from the table A3, the results are very similar to the baseline. We obtain the same order of magnitude for all estimated

[16] The most important crops (corn, rice, beans and sugarcane) are cultivated in this season.

coefficients, as well as for standard errors. The only exception is share of hours spent in agricultural main job on the total, where the estimated coefficients of interest are not significant. However, this result may be due to low statistical power given the reduced sample size. Point estimates are fact very similar to the baselines and we cannot reject the null hypothesis that both estimates are the same.

Second, as discussed above, if different families are more likely to respond to rainfall shocks by migrating, one would expect to see significant effects of rainfall shocks on predetermined characteristics. To explore this issue, Table A4 estimates whether rainfall shocks are associated with any individual or household characteristics for all economically active population in our sample. All regressions results are based on a specification that adjust for municipality fixed effects, year fixed effects and are clustered at the municipality level. Columns (1) to (3) assess estimates of the effect of rainfall negative shocks on the head of household characteristics such as age, gender and education. Column (4) shows estimates for family size as dependent variable. Out of four estimated coefficients of interest, none is statistically significant. Thus, there is little evidence that our baseline results are in fact driven by migration.

Rainfall variation across space and time should generate corresponding variation in agricultural output and thus should mainly have a bigger effect in rural areas rather than urban. To assess if this occur in Northeastern Brazil, we examine the effect of drought shocks on labor outcomes of urban households. Table A5 presents the estimates for this subsample. As can be seen from the table, there is no significant effect of negative rainfall shocks on urban labor outcomes; most effects are concentrated in rural areas.

6. Conclusion

It is already well documented in the literature the acute vulnerability of developing countries to extreme weather events. Water scarcity is a major problem for a large fraction of the rural population in these countries. Climate change is likely to make it an even more recurrent phenomenon in the coming decades. Considering the economic situation of most rural households in developing countries, adaptation will play a limited role in mitigating the impacts of climate change on agricultural production. Thus, this paper investigates the effects of drought shocks on rural household non-agricultural labor supply.

Reducing the variability of agricultural income streams is of paramount importance to improve welfare of rural dwellers. Given the constraints faced in the insurance and credit markets by most rural families in developing countries, labor reallocation can be one of the main channels by which poor rural households mitigate negative rainfall shocks. Engaging in non-farm labor market might help households to smooth income.

The strategy outlined here presents evidence of a relationship between negative rainfall events and labor time reallocation. We find that drought shocks are significantly associated with lower income derived from the main job. This is especially true when we consider income derived from farm activities. Moreover, higher incidence of drought shocks are significantly associated with increased income from secondary jobs. Our results show that droughts affect negatively hours spent on farm work, whereas lead to increased supply of non-agricultural job. One can also observe stronger effects among families residing in municipalities with lower per capita income. Taken together, our findings suggest that rural families adjust labor supply as an autonomous strategy in order to mitigate the income effects of water scarcity.

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Appendix

Table A1. Effect of drought shocks on rural household labor outcomes

	(1) Number of Jobs	(2) Share of farm employement	(3) Share of secondary employment	(4) Share of household farm employment	(5) Share of household secondary employment	(6) Non-farm employment
Drought shock (SPI) Feb/April	0.0303 [0.0211]	-3.7929 [1.4891]**	1.5246 [0.8157]*	-2.2129 [1.5053]	1.21 [0.6598]*	0.0093 [0.0172]
Mean of dep. Var	0.11	69.5	4.37	65.9	3.47	0.37
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Temperature controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
N	40006	40006	40006	42952	42952	47295
R-sq	0.129	0.176	0.121	0.181	0.123	0.116

Notes: Each coefficient is from a different regression. All regressions control for municipality and year fixed effects. Columns (1) to (3) measure the outcomes at the head of household level, while in columns (4) to (6) the outcomes are at the household level. Each dependent variable in columns (2) to (5) refers to the share of the mentioned work on the total of hours worked. Basic controls include gender, age, race and family size. Temperature control include the average temperature at municipality level. Robust standard errors (reported in brackets) are clustered at the municipality level. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A2. Effect of consecutive drought shocks on rural household labor outcomes

	(1) Number of Jobs	(2) Share of farm employement	(3) Share of secondary employment	(4) Share of household farm employment	(5) Share of household secondary employment	(6) Non-farm employment
2-or more consecutive drought shock	0.0218 [0.0079]***	-1.7375 [0.8566]**	0.9026 [0.3240]***	-1.582 [0.8891]*	0.6522 [0.2599]**	0.0028 [0.0086]
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Temperature controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
N	40006	40006	40006	42952	42952	47295
R-sq	0.129	0.177	0.121	0.182	0.122	0.116

Notes: Each coefficient is from a different regression. All regressions control for municipality and year fixed effects. Columns (1) to (3) measure the outcomes at the head of household level, while in columns (4) to (6) the outcomes are at the household level. Each dependent variable in columns (2) to (5) refers to the share of the mentioned work on the total of hours worked. Basic controls include gender, age, race and family size. Temperature control include the average temperature at municipality level. Robust standard errors (reported in brackets) are clustered at the municipality level. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A3. Effect of drought shocks on labor outcomes for rural household living at least five years in currently municipality

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of Jobs	Share of farm employement	Share of secondary employment	Share of household farm employment	Share of household secondary employment	Non-farm employment
Drought (SPI)	0.0068 [0.0031]**	-0.2467 [0.3763]	0.2926 [0.1189]**	-0.294 [0.4557]	0.2254 [0.0921]**	-0.0029 [0.0046]
Mean of dep. var.	0.11	65.4	4.55	61.67	3.62	0.41
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Temperature controls	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
N	11048	11048	11048	12012	12012	13166
R-sq	0.146	0.248	0.136	0.251	0.137	0.158

Notes: Each coefficient is from a different regression. All regressions control for municipality and year fixed effects. Columns (1) to (3) measure the outcomes at the head of household level, while in columns (4) to (6) the outcomes are at the household level. Each dependent variable in columns (2) to (5) refers to the share of the mentioned work on the total of hours worked. Basic controls include gender, age, race and family size. Temperature control include the average temperature at municipality level. Robust standard errors (reported in brackets) are clustered at the municipality level. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A4. Effect of drought shocks on rural households predetermined characteristics

	(1)	(2)	(3)	(4)
	Age	Gender	Education	Family Size
Drought (SPI)	-0.0227 [0.0488]	-0.0024 [0.0029]	-0.0032 [0.0155]	-0.0164 [0.0135]
Temperature controls	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
N	92006	92006	92006	92006
R-sq	0.017	0.008	0.084	0.061

Notes: Each coefficient is from a different regression. All regressions control for municipality and year fixed effects. Temperature control include the average temperature at municipality level. Robust standard errors (reported in brackets) are clustered at the municipality level. Significance: * p < 0.10, ** p < 0.05, *** p < 0.01.

Table A5. Effect of drought shocks on urban households

	(1)	(2)	(3)	(4)	(5)	(6)
	Number of Jobs	Share of farm employement	Share of secondary employment	Share of household farm employment	Share of household secondary employment	Non-farm employment
Drought (SPI)	0.001 [0.0009]	-0.043 [0.1839]	0.0318 [0.0372]	-0.0258 [0.1675]	0.0242 [0.0285]	0.0016 [0.0015]
Mean of dep. Var	0.06	8.29	2.31	6.92	2.06	0.81
Basic controls	Yes	Yes	Yes	Yes	Yes	Yes
Temperature controls	Yes	Yes	Yes	Yes	Yes	Yes
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
N	123292	123292	123292	145416	145416	170024
R-sq	0.023	0.149	0.02	0.123	0.02	0.122

Notes: Each coefficient is from a different regression. All regressions control for municipality and year fixed effects. Columns (1) to (3) measure the outcomes at the head of household level, while in columns (4) to (6) the outcomes are at the household level. Each dependent variable in columns (2) to (5) refers to the share of the mentioned work on the total of hours worked. Basic controls include gender, age, race and family size. Temperature control include the average temperature at municipality level. Robust standard errors (reported in brackets) are clustered at the municipality level. Significance: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.