

# Long-term Consequences of Droughts in Brazil

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## Abstract

It is well-documented that droughts can have a severe impact on the welfare of rural households in developing countries. We find there is long-term damage far beyond the immediate impact of the drought with affected households taking a decade to catch up with their peers. Our findings are robust to the specification of the drought and the assumed time-frame of the impact. Upon stratifying by wealth, the results indicate that the lowest twenty-five percent and middle fifty percent income households are most affected by droughts. Designers of emergency relief and drought-mitigation policies will benefit from future investigation into the causes of pervasive, drought-induced income losses.

JEL Classification: O12, I32

*Key words:* Droughts, risk, long-term impact, household income

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# 1 Introduction

Natural disasters are prevalent in low-income countries, destroying the livelihoods of large fractions of the populations. In 1991-2005, approximately 1 billion people were affected by droughts—most residing in developing countries (UNISDR, 2005). Recently, scientists have indicated that the prevalence of droughts may increase with global warming (Dai et al., 2004). Of policy interest is the long-term losses of droughts, particularly to designers of emergency relief, drought-mitigation policies, and climate change policies. Regarding the latter, a gap remains in the climate change valuation literature in addressing droughts. The literature has focused on the impacts in changes of U.S. long-term mean climate variables rather than changes in their extreme counterparts.<sup>1</sup>

Do the consequences of drought extend beyond the immediate event into the long-term? Recently, studies have begun to document the severe impact of droughts on the long-term welfare of households in a limited number of drought-prone villages (Dercon, 2004). We consider whether the damages are of sufficient scale to be evident in national datasets. We estimate a reduced-form wage model to detect the long-term consequences of droughts on household wages in Brazil. An additional contribution of our study is that it extends the analysis to include both rural and urban labor markets. We find that this long-term effect is long lasting with affected households taking a decade to catch up with their peers.

We use the 1992 and 1995 Brazilian national survey of sampled households and University of East Anglia Climate Research Unit historical monthly climate precipitation data to measure the wage impact of droughts over time. The demographic and income data consist of two cross-sections of approximately 165,000 households living in both rural and urban municipalities of Brazil. The geographic scope of the household surveys allows for the comparison of drought impacts across regional markets with varying resources for drought mitigation and climate change adaptation. We apply an identification strategy that relies on variation between cross-sectional surveys from two different years in order to test if there is evidence of long-lasting impacts of drought in a reduced-form analysis of national household data. We do not attempt to establish the mechanisms through which these impacts occur. Although the dataset is quite extensive in scope and magnitude, our identification strategies are, of course, limited due to the primarily cross-sectional nature of the data. Additionally, our analysis is not

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<sup>1</sup>The importance of examining the impact of future changes in U.S. climate variability recently is noted by Schlenker and Roberts (2006). While Deschenes and Greenstone (2006) find little to no effect of future changes in mean climate variables on U.S. crop yields, Schlenker and Roberts (2006), in contrast, predict substantial future losses in U.S. crop yields from changes in extreme temperatures.

conducive for understanding the nature of the causes of the wage losses. The survey offers a substantial amount of information regarding labor conditions for each household, but lacks information regarding household portfolio choices, assets, and other variables that could be used to characterize household idiosyncratic risks.

Our study focuses on Brazil, since it historically experienced substantial damages from droughts. Since 1948, the most severe drought occurred in 1983 affecting 20 million people (or 16 percent of the 1983 Brazilian population) (EM-DAT, 2006). Overall estimates of the cumulative economic damages of droughts from 1948-2006 are reported to be 4.7 billion US dollars (approximately 0.8 percent of Brazil's 2005 GDP) (EM-DAT, 2006).

In our analysis, we characterize wage equilibrium effects of past droughts by using two different sets of measures. Our first set of lagged drought variables are the number of standard deviations below the municipality precipitation mean that occurred one year ago, two years ago, and so on. We compare regressions that include the first set of lagged drought variables assuming ten-year and twenty-year lagged specifications. The second set of lagged drought variables are a set of dummy variables for whether the precipitation value one year ago, two, years ago, and so on, was within the first state percentile. We apply the second set of lagged drought dummy variables assuming ten-year and twenty-year lagged specifications. We find that household wages, particularly in rural areas, decline for approximately ten years following a drought. Our findings are robust to the specification of the drought and the assumed time-frame of the impact.

Finally, we stratify the regression results by three wealth groups (low twenty-five percent, middle fifty percent, and top twenty-five percent) to test whether vulnerability to droughts depends on wealth. We find that the top twenty-five percent are largely unaffected by these droughts. Both the low twenty-five percent and middle fifty percent suffer losses in wages five years post the drought. The middle fifty percent income households face longer recovery periods. Though explaining the reasons behind effects is beyond the scope of our study, this may be due to the lack of targeted government intervention programs towards this class, or the greater potential for loss of capital among the middle class. These findings may also lend support to claims made by other social scientists that existing rural welfare programs in northeastern Brazil have the tendency to expand the adaptation strategies of low-income rural households (Finan and Nelson, 2001).

## 2 Literature Review

A vast literature exists measuring the ability of households to smooth consumption when facing shocks to productivity and short-term income (Kazianga and Udry, 2004; Jalan and Ravallion, 1999; Alderman and Paxson, 1994; Townsend, 1994; Deaton, 1992; Paxson, 1992; Deaton, 1991; Zeldes, 1989). The empirical evidence lends support for partial insurance. Households are unable to smooth fluctuations in income by saving during periods of high income and borrowing during periods of low income. Thus, households experience a welfare loss induced by their inability to maintain a given level of consumption over a short period of time.

Additional studies offer explanations for the persistent effects of shocks on long-term income, and why the effects may vary by wealth. Eswaran and Kotwal (1990) examine the case of individuals who are risk averse to an uneven consumption profile over time. Credit-constrained households are more likely to accept a loss in mean income in exchange for lower income variance. Rosenzweig and Binswanger (1993) provide a similar argument for the case where households face covariate risk, i.e. shocks faced by all households in a given location. Borrowing resources become limited under these circumstances. The paucity of credit institutions leads low-income households to invest in less risky portfolios. Moreover, conservative portfolio choices among low-income households perpetuate the inequitable distribution of income, as risky portfolios on average yield higher returns.

Rosenzweig and Wolpin (1993) posit Indian farmers underinvest in their productive assets. In their example, bullocks generate wealth to farmers in their contribution to production, and also in terms of their sales value when facing substantial crop losses. The underinvestment in bullocks has severe implications for poor farmers who during a shock face output and income losses.

Jayachandran (2005) attributes losses in equilibrium wages to the presence of an inelastic labor supply during a negative productivity shock. The inelastic labor supply results from workers supplying more labor to satisfy consumption instead of borrowing or migrating to labor markets unaffected by the shock. Wage regressions reveal small losses experienced by low-income households in Indian districts with fewer credit institutions and higher migration costs.

Santos and Barrett (2006) investigate the relationship between climate shocks and wealth of Ethiopian pastoralists to detect the source of poverty traps. They attribute the extant poverty to pastoralists' inability to protect assets from adverse shocks. A critical determinant of long-term wealth implications of shocks is herder

ability. They conclude that this identification can be used to target the recipients of future assets transfers.

In this paper, we use a reduced-form wage model to detect the lasting effect of past precipitation shocks, with a particular focus on droughts, on household wages in Brazil. The aforementioned work address the ex ante underinvestment due to the potential for weather-related income risk instead of the ex post loss from climate events. Our studies expands upon this body of work in that we attempt to estimate the ex post impact from uninsured risk.

Only recently have studies begun to investigate the long-term consequences from droughts. Dercon (2004) employs a standard empirical growth model to examine the persistence of losses from drought on food consumption in Ethiopia. He explains that a loss in physical and social capital arises from households inability to insure themselves when facing a shock, therefore, reducing their set of future income generating activities. He uses a panel data set to explicitly measure the association between growth rates in food consumption and lagged rainfall shocks. The empirical model indicates that a ten percent decrease in rainfall four to five years earlier led to a one percent decline in current growth rates (Dercon, 2004).

Our paper addresses some of the limitations of previous work. First, we expand the spatial scope of our analysis to all households living in rural areas of Brazil. The results based on our sample of rural households is more generalizable to the national level, as these households are not selected based on their level of drought vulnerability.

Second, we examine the impact of climate shocks on urban households in addition to rural households. The mechanisms by which climate shocks affect rural households has been rigorously examined. Few studies estimate the impacts of climate shocks on urban households in developing countries.<sup>2</sup> Households in urban areas in developing countries may experience greater damages from climate variability than in most industrialized countries due to the lack of resources to overcome the climate shock and the nature of their production. In fact, many urban residents are construction workers and street vendors, which may be extremely dependent on water availability

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<sup>2</sup>In the hedonic valuation literature, there are a few studies that measure the impact of changes in mean climate variables on urban incomes in industrialized countries for the purpose of measuring the damages of global warming (Hoch and Drake, 1974; Nordhaus, 1996; Cragg and Kahn, 1997; Maddison and Bigano, 2003). These studies presume that the urban wage effects capture the welfare impact from changes in climate. This is true as long as climate is neutral to production costs (Roback, 1982). Firms in urban areas of developing countries, however, may be more vulnerable to changes in climate as they have less resources to mitigate the effect of climate on production and the initial conditions of tropical climate are more severe. Thus, in the developing country context, similar work measuring the impact of changes in climate on urban wages may be measuring the effect from productivity losses in addition to benefits or costs to household welfare.

and the production of agricultural goods.<sup>3</sup> Droughts could limit a construction worker’s capacity to build or vendor’s ability to sell, increasing production costs in these sectors. One of our aims is to detect whether there are deleterious long-term consequences of droughts in urban areas (despite the many infrastructural advantages that may exist in these areas) to warrant future investigation into the mechanisms by which these households are affected.

Third, we also measure how sensitive the wage losses are to the distribution of wealth. The aforementioned studies suggest that the impact of droughts should vary with wealth for several reasons, which include differences in risk aversion, portfolio choices, investment in productive assets, and asset protection. We consider the disparate wage effects of droughts by stratifying the sample in our analysis by wealth group (low twenty-five percent, middle fifty percent, and top twenty-five percent).

### 3 Data

We use two available Brazilian households surveys administered by the Brazilian government, the 1992 and 1995 Pesquisa Nacional de Amostra Domicilios (PNAD). Approximately 80,000 and 85,000 households were sampled in the 1992 and 1995 surveys, respectively. The PNAD questionnaire collects a variety of information regarding demographics and wages for each member of the households sampled. This information is georeferenced to the municipality level using Brazilian GIS data (IBGE, 1998).

To formulate our drought variables, we use the University of East Anglia Climate Research Unit monthly precipitation data.<sup>4</sup> The data are interpolated from 13,197 weather stations to provide a comprehensive georeferenced grid of climate indicators at a 0.5 degree spatial resolution (New et al., 2000). The resolution is at a convenient scale for our municipality level household data.

We use the precipitation data to construct two measures of droughts. The first measure is the number of standard deviations below the precipitation mean. Using this measure, we create lagged precipitation variables

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<sup>3</sup>Approximately 650 thousand Brazilians worked in the construction industry out of 10.3 million employed individuals at least 20 years of age in the greater metropolitan areas of Recife, Salvador, Belo Horizonte, Rio de Janeiro, Sao Paulo, and Porto Alegre in 1991 (IBGE, 2006). This is slightly greater than the percentage of U.S. workers in the construction industry in the greater metropolitan areas of Los Angeles, District of Columbia, Miami, Chicago, Boston, and New York, for example, in 2004 (921 thousand of 23.4 million workers) (BLS, 2006).

<sup>4</sup>The data are available from the International Research Institute for Climate and Society’s Data library available at [iri.columbia.edu](http://iri.columbia.edu).

with a lag length of ten years for each household using annual precipitation data from 1972-1994,  $R_{t-n}$ ,  $t \in \{1992, 1995\}$ ,  $n \in \{1, 2, \dots, 10\}$ , where  $t$  indicates the census year and  $n$  indicates the number of years ago. We experiment with the time frame of the drought impact in our regression analysis by also using an alternative specification of our first measure of droughts. We extend the time frame to twenty years, but this time include four variables that represent the average number of standard deviations below the precipitation mean over four five-year periods:  $R_{ti}$ ,  $i \in \{0, 1, 2, 3\}$ ,  $R_{ti} = \frac{1}{5} \sum_{n=5i+1}^{5i+5} R_n$ , where  $R_n$  is the number of standard deviations below the precipitation mean  $n$  years ago. We compare the results from regressions that include the first ten precipitation variables and five-year averages of the twenty variables.

The second drought measure is a dummy variable indicating if the municipality's precipitation is in the first percentile of the distribution of state precipitation levels. We calculate the state percentiles using annual precipitation data from 1950-2002. Using this measure, we create ten lagged dummy variables for each household,  $D_{t-n} = 1$  if the precipitation level  $n$  years ago is in the first percentile of the distribution of state precipitation levels,  $t \in \{1992, 1995\}$ ,  $n \in \{1, 2, \dots, 10\}$ , otherwise  $D_{t-n} = 0$ . As with the first drought measure, we create an additional group of variables to experiment with the time frame of the drought impact in our regression analysis. We create four dummy variables that take the value one if the precipitation values for at least one year within four five-year time frames was in the first percentile of the state distribution:  $D_{ti} = 1$ ,  $i \in \{0, 1, 2, 3\}$ , if  $D_i > 0$ ,  $D_i = \sum_{n=5i+1}^{5i+5} D_n$ , otherwise  $D_{ti} = 0$ .

In sum, there are four different groups of variables that we use to characterize droughts and the timing of the impact. These different sets of variables are summarized in Table 1. Averages for the precipitation shock variables are displayed by location and census year in Table 2.

### 3.1 Missing income

In our survey, twelve percent of the households did not report labor income. Any inferences we make based on our wage regression may be subject to sample selection bias. We present the averages of the demographic variables by location<sup>5</sup> and income response in Table 3 to observe any fundamental differences between samples. The households that do not report any labor income tend to be smaller in size, and generally have members that

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<sup>5</sup>Municipalities are considered rural if the population is less than fifty thousand, otherwise they are defined urban.

Table 1: Description of Drought Variables

Definition	Variable
Standard deviations below the mean (short time frame)	
1 year ago	$R_{t-1}$
2 years ago	$R_{t-2}$
3 years ago	$R_{t-3}$
4 years ago	$R_{t-4}$
5 years ago	$R_{t-5}$
6 years ago	$R_{t-6}$
7 years ago	$R_{t-7}$
8 years ago	$R_{t-8}$
9 years ago	$R_{t-9}$
10 years ago	$R_{t-10}$
Standard deviations below the mean (long time frame)	
Average over 1-5 years ago	$R_{t0}$
Average over 6-10 years ago	$R_{t1}$
Average over 11-15 years ago	$R_{t2}$
Average over 16-20 years ago	$R_{t3}$
Dummy variable for first percentile (short time frame)	
1 year ago	$D_{t-1}$
2 years ago	$D_{t-2}$
3 years ago	$D_{t-3}$
4 years ago	$D_{t-4}$
5 years ago	$D_{t-5}$
6 years ago	$D_{t-6}$
7 years ago	$D_{t-7}$
8 years ago	$D_{t-8}$
9 years ago	$D_{t-9}$
10 years ago	$D_{t-10}$
Dummy variable for atleast one year in the first percentile (long time frame)	
1-5 years ago	$D_{t0}$
6-10 years ago	$D_{t1}$
11-15 years ago	$D_{t2}$
16-20 years ago	$D_{t3}$



Table 2: Averages of Precipitation Shock Variables by Location and Census year

Census Sample	1992 Urban	1995 Urban	1992 Rural	1995 Rural	1992 All	1995 All
Standard deviations below the mean						
1 year ago	0.361	0.178	0.412	0.224	0.377	0.192
2 years ago	0.538	0.516	0.684	0.703	0.585	0.575
3 years ago	0.188	0.271	0.110	0.264	0.163	0.269
4 years ago	0.240	0.363	0.357	0.408	0.277	0.377
5 years ago	0.207	0.545	0.301	0.697	0.237	0.592
6 years ago	0.171	0.179	0.188	0.110	0.176	0.158
7 years ago	0.487	0.239	0.475	0.355	0.483	0.275
8 years ago	0.669	0.216	0.547	0.299	0.630	0.242
9 years ago	0.377	0.172	0.400	0.193	0.385	0.179
10 years ago	0.138	0.478	0.295	0.468	0.188	0.475
Standard deviations below the mean						
Average over 1-5 years ago	0.307	0.375	0.373	0.459	0.328	0.401
Average over 6-10 years ago	0.369	0.257	0.381	0.285	0.373	0.266
Average over 11-15 years ago	0.434	0.429	0.346	0.393	0.406	0.418
Average over 16-20 years ago	0.290	0.365	0.242	0.302	0.275	0.345
Dummy variable for first percentile						
1 year ago	0.000	0.001	0.000	0.002	0.000	0.001
2 years ago	0.003	0.011	0.010	0.050	0.005	0.023
3 years ago	0.001	0.000	0.000	0.000	0.001	0.000
4 years ago	0.001	0.000	0.000	0.000	0.001	0.000
5 years ago	0.000	0.004	0.000	0.012	0.000	0.006
6 years ago	0.001	0.001	0.000	0.000	0.001	0.001
7 years ago	0.053	0.001	0.044	0.000	0.050	0.001
8 years ago	0.020	0.000	0.011	0.000	0.017	0.000
9 years ago	0.006	0.001	0.018	0.000	0.010	0.001
10 years ago	0.001	0.054	0.004	0.044	0.002	0.051
Dummy variable for atleast one year in the first percentile						
1-5 years ago	0.006	0.012	0.010	0.055	0.007	0.025
6-10 years ago	0.082	0.057	0.075	0.044	0.079	0.053
11-15 years ago	0.038	0.063	0.016	0.044	0.031	0.057
16-20 years ago	0.005	0.002	0.011	0.015	0.007	0.006
Observations	46927	51387	21922	23391	68849	74778

are considerably older than households that reported income. Heads of households that do not report income tend to be older, averaging fifty-nine years. These individuals are likely at a different stage in the life cycle than those that report income. Older heads of households may be benefiting from government or private sector retirement stipends which continue to flow independent of adverse precipitation shocks. Thus, it is likely that these households are less vulnerable to shocks than wage earning households. Although it is not the main focus of our analysis, we consider the impact of sample selection bias by estimating a Heckman model to see if our results are robust.

There are few differences in the demographic characteristics between urban and rural households. The most striking difference is in monthly household wages, where the value for the average rural household is 52 percent of that for the average urban household. Another prominent difference lies in the spatial variation between samples. Thirty-three percent of the urban households lives in the northern region, whereas forty percent of the rural sample lives in the northern region. Excluding the midwestern region, fifty-seven percent of the urban sample of households lives in the southern region compared to forty-six percent of the sample of rural households. While these differences are noteworthy, there is still a substantial representation and variation regionally in both samples to isolate the impact of drought on wages from regional unobservables, such as poverty.

### **3.2 Droughts and recessions**

A final consideration regards the timing of the surveys and droughts. The challenge we face in identifying the effect of past adverse precipitation shocks on income is the concurrent events of precipitation shocks and economic recessions. For example, there were five severe economic recessions alone in the period of 1987 to 1992 (Chauvet, 2002), and quite a few dry periods.<sup>6</sup> We include state fixed effects and define the shock variables in terms of "timing years ago", rather than specific years, to differentiate between the effects of recessions and precipitation shocks on household wages.

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<sup>6</sup>Figure 1 compares the 1980-2005 trend of precipitation (indexed from negative one to one) in the northern and southern regions of Brazil. From the figure, it is clear that both the northern and southern regions experienced quite a few dry periods during that period.

Table 3: Averages of Demographic Variables by Location and Income Response

Sample	Urban	Urban	Rural	Rural	All	All
Report Income?	Yes	No	Yes	No	Yes	No
Monthly wage (1995 Reais)*	877.925	0.000	451.764	0.000	743.475	0.000
Head of household's age	42.598	57.875	43.928	60.486	43.018	58.747
No. of hhd. members by age category						
15-25	0.899	0.331	0.917	0.416	0.905	0.326
26-35	0.705	0.244	0.647	0.231	0.687	0.240
36-45	0.542	0.194	0.484	0.176	0.523	0.188
46-55	0.323	0.229	0.334	0.178	0.327	0.212
greater than 55	0.308	0.918	0.374	0.964	0.329	0.934
Northern region						
Rondonia	0.007	0.004	0.006	0.004	0.007	0.004
Acre	0.003	0.002	0.002	0.001	0.003	0.002
Amazonas	0.015	0.011	0.007	0.005	0.012	0.009
Roraima	0.002	0.001	0.001	0.001	0.002	0.001
Para	0.037	0.024	0.015	0.014	0.030	0.021
Amapa	0.003	0.001	0.001	0.001	0.002	0.001
Tocantins	0.002	0.002	0.027	0.024	0.010	0.009
Northeastern region						
Maranhao	0.007	0.008	0.035	0.046	0.016	0.021
Piaui	0.010	0.009	0.021	0.031	0.013	0.016
Ceara	0.055	0.044	0.054	0.059	0.055	0.049
Rio Grande do Norte	0.008	0.009	0.026	0.027	0.014	0.015
Paraiba	0.012	0.014	0.026	0.044	0.017	0.024
Pernambuco	0.070	0.089	0.045	0.064	0.062	0.080
Alagoas	0.012	0.012	0.014	0.012	0.013	0.012
Sergipe	0.012	0.017	0.019	0.023	0.014	0.019
Bahia	0.072	0.077	0.100	0.150	0.081	0.101
Southeastern region						
Minas Gerais	0.107	0.098	0.140	0.137	0.117	0.111
Espirito Santo	0.014	0.013	0.025	0.018	0.017	0.015
Rio de Janeiro	0.118	0.153	0.020	0.022	0.087	0.109
Sao Paulo	0.155	0.162	0.083	0.076	0.131	0.135
Southern region						
Parana	0.062	0.052	0.074	0.060	0.066	0.055
Santa Catarina	0.018	0.014	0.047	0.033	0.028	0.020
Rio Grande do Sul	0.100	0.117	0.074	0.056	0.092	0.096
Midwestern region						
Mato Grosso do Sul	0.014	0.009	0.031	0.019	0.019	0.012
Mato Grosso	0.013	0.007	0.039	0.021	0.021	0.012
Goias	0.034	0.027	0.068	0.052	0.045	0.035
Distrito Federal	0.038	0.024	0.000	0.000	0.026	0.016
Observations	98314	13197	45313	6614	143627	19811

\* The 1992 monthly wage data were converted into 1995 Reais using the Consumer Price Indexes from the International Monetary Fund (IMF, 1993, 1996).

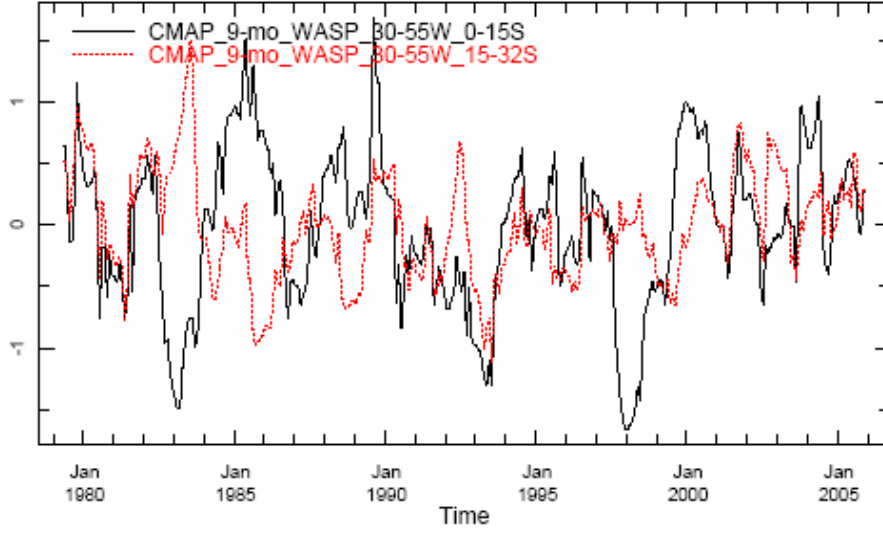


Figure 1: Precipitation Anomalies in the North and South of Brazil

## 4 Econometric Model

We estimate four reduced-form monthly household wage regressions, which include (i) four dummy variables indicating the occurrence of droughts within five-year time periods over twenty years, (ii) ten dummy variables indicating the occurrence of annual droughts over ten years, (iii) the average number of standard deviations below the precipitation mean within five-year time periods over twenty years, and (iv) the annual number of standard deviations below the precipitation mean over ten years:

$$\log y_{hjt} = \alpha_0 + \alpha_j + \alpha_{1992} + \sum_{i=0}^3 \gamma_i D_{j,ti} + \sum_{k=1}^K \beta_k X_{hk} + \varepsilon_{hjt}. \quad (1)$$

$$\log y_{hjt} = \alpha_0 + \alpha_j + \alpha_{1992} + \sum_{n=1}^{10} \gamma_n D_{j,t-n} + \sum_{k=1}^K \beta_k X_{hk} + \varepsilon_{hjt}, \quad (2)$$

$$\log y_{hjt} = \alpha_0 + \alpha_j + \alpha_{1992} + \sum_{i=0}^3 \gamma_i R_{j,ti} + \sum_{k=1}^K \beta_k X_{hk} + \varepsilon_{hjt}, \quad (3)$$

$$\log y_{hjt} = \alpha_0 + \alpha_j + \alpha_{1992} + \sum_{n=1}^{10} \gamma_n R_{j,t-n} + \sum_{k=1}^K \beta_k X_{hk} + \varepsilon_{hjt}, \quad (4)$$

We compare the estimates from these regressions that differ by the specification of droughts and timing of the impact to evaluate the robustness of our results.

All regressions include the head of household's age, the head of household's age-squared, and the number of household members in five age categories, controlling for features of household labor supply. The head of household's age reflects the work experience of the primary income earner. The number of household members in five age categories may proxy the level of savings or assets a household possesses (Paxson, 1992). Paxson notes that households with younger children and older adults may save less, especially if parents' spending on children is a substitute for savings. Depleting savings and assets are alternative strategies to coping with income risk.

State  $\alpha_j$  and survey  $\alpha_{1992}$  fixed effects capture the effect of unobservable spatial and time variables that influence wages. The last term  $\varepsilon_{hjt}$  (where  $h$ ,  $j$ , and  $t$  index the household, state, and survey year, respectively) in regressions (1)-(4) represents the idiosyncratic error term. The parameter and standard error estimates are computed using the household population weights provided by the PNAD survey for all specifications of model.

## 5 Results

### 5.1 Droughts Measured by Low-Probability Negative Precipitation Shock Occurrences

Our results show robust evidence of long-term negative impacts of droughts. Beginning with regression equation (1), we observe droughts depressing wages ten years after the incident in both rural and urban labor markets (see Table 4). After ten years, rural and urban wages appear to benefit from the shock which may be due to the return on drought-induced government investments, which increase local productivity, and thus, wages, in the long-term. In Northeastern Brazil, for example, the World Bank during the 1980s financed several projects to reduce vulnerability to drought by providing resources such as water, access to credit, education and health care (Finan and Nelson, 2001). The qualitative evidence to support the sign and significance of the 16 to 20 years ago parameters in the urban and rural wage models is limited. Obviously, in the 16 to 20 year time frame, it is likely that the parameter estimates may be spurious given the potential for uncontrolled structural changes.

We restrict our measurement of the long-term effects of shocks to a ten-year period, disaggregating the

initial five-period time frames to single years. The results from regression (2) are displayed in Table 5 and remain consistent with those from regression (1). The coefficients that are significant at the five percent critical level in the urban regression are all negative with the exception of the ten years ago parameter. In the rural regression, there were isolated years which did not experience precipitation levels within the state's first percentile. Nevertheless, all coefficients in the rural regression are negative and significant at the one percent critical level save one, the 8 years ago variable.

Next, we estimate regressions (1) and (2) accounting for sample selectivity, recognizing that omitting a non-random fraction of our sample from the analysis due to missing data on income may bias our results (see Tables 6 and 7). The selection equation includes a constant, head of household's age, head of household's age squared, and three dummy variables indicating whether the household had at least one person receiving a pension, remittances, or dividends from an investment. All six coefficients were significant at the five percent critical level. The head of household's age, dividends dummy variable, and constant parameters have positive signs. The head of household's age squared, and pension and remittance dummy parameters have negative signs. The selection equation regression results support our conclusions regarding the demographics of the sample missing household income. The parameter estimates of the Heckman wage regressions are similar to their OLS counterparts with slight changes in magnitude on the order of 0.001. The Heckman model results imply our wage findings are robust to the omission of households missing income data.

We perform a final test to formally measure the impact of wealth on the ability to mitigate the damages from shocks on income. We employ regression model (1). From Table 8, without differentiating labor markets by region, it is evident that the low twenty-five percent income households in our sample are hit harder by the drought in magnitude, yet both low and middle income tiers benefit in the 11 to 15 year time frames.<sup>7</sup> The results from these models are consistent with the models that do not stratify by wealth. However, an interesting finding remains in the regression that includes the top 25 percent income households. Essentially, the wealthier class are not affected by droughts in the first ten years, but potentially benefit afterwards perhaps from the investments that were made in response to the event.

Upon stratifying regression equations (1) and (2) by wealth and region, the findings corroborate earlier studies

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<sup>7</sup>The low 25 percent, middle 50 percent, and top 25 percent income households are defined according to the regional distributions of income.

demonstrating the rural poor’s vulnerability to shocks due to credit constraints, underinvestment, or risk aversion (Eswaran and Kotwal, 1990; Rosenzweig and Binswanger, 1993; Jayachandran, 2005) (see Tables 9 and 10). Rural low-income workers incur wage losses in the first five years, but are able to recover more quickly than the middle class. The wealthiest class in the rural areas are unaffected by the droughts. The evidence supports Finan and Nelson’s claim that existing welfare programs provide flexibility in coping with droughts. The middle class may require a longer recovery from the shock, perhaps due to their lack of government financial assistance, access to credit, or a greater potential for loss of capital.

The regression results are less conclusive when we focusing on urban labor markets stratified by household wealth and when estimating regression equation (2). In regression equation (2), what remains robust is the regressions’ lack of explanatory power for the top twenty-five percent income households. Clearly, the upper income tier is less vulnerable to the income variability caused by droughts.

## **5.2 Droughts Measured by the Number of Standard Deviations Below the Precipitation Mean**

Regressions (3) and (4) include less conservative measures, the number of standard deviations below the precipitation mean, in contrast to the drought dummy variables used in the previous section. Tables 11 and 12 display the results from regressions (3) and (4). Using the alternative measure of droughts produces similar wage effects over a ten-year time frame, as did our original drought specification. The auxiliary specification however yields different parameter estimates for the longer-term precipitation variables.

Table 12 presents the results from regression (4). We restrict this model to a ten-year time frame as we recognize the variables from the latter years may be less reliable and the correlation potentially spurious. The results from regression equation (3) corroborate the findings from regression (4). All signs are negative and significant at the five percent critical level in the urban regression, with the exception of the 3 years ago and 10 years ago parameters. The empirical results from the rural regression are also the same as those in regression (3), with the exception of the 8 years ago parameter. As in regressions (1) and (2), our findings are robust upon accounting for sample selectivity (see Tables 13 and 14).

Next, we stratify the regressions (3) and (4) by wealth. The results from regression (3) stratified by wealth

demonstrate that all three income classes are negatively impacted by the drought in the initial five years post the drought, and recovery takes place after the tenth year. These results are also consistent with our earlier findings. Table 15 shows the same wage regressions stratified by wealth and region. The rural regression results remain consistent with our expectations and findings from the previous models. That is, all classes are impacted in the first ten years, with the poor and middle income classes incurring greater losses in wages.

Our final regression estimates equation (4) stratified by wealth and region. The results in Tables 16 and 17 do not deviate from the those of the previous models. Specifically, low and middle income households are negatively affected by droughts when pooling and distinguishing between regional labor markets.

## 6 Conclusion

We use two cross-sectional household surveys to identify the long-term impacts of droughts on household wages. Two measures of droughts were applied and different definitions of “long-term” were assumed. All models support a decline in households wages ten years following the shock on a national scale.

We also expanded the scope of the analysis from rural households to both rural and urban households. The results indicate that urban households are also negatively impacted by droughts. Our evidence suggest the value in extending the coping literature to urban areas and investigating the mechanisms that drives the losses in those labor markets and production processes.

We also stratified the sample by wealth to test whether inabilities to cope with shocks associated with inequities in income cause differential drought effects on wages. The evidence shows that the low twenty-five percent and middle fifty-percent income households are most affected by droughts, with a longer trial period experienced by the middle income class. While many studies highlight the inability of low-income households to fully insure themselves against shocks, few studies compare income groups abilities to self-insure against shocks and explore the role of government welfare programs in expanding the range of coping strategies for the poor.

Our results demonstrate that there are long-term negative effects on wages attributed to severe droughts. The dataset limited our ability to investigate the causes of the pervasive wage losses (e.g., poor or short-sighted coping strategies, or those suggested in earlier work). Future research could reveal the reasons for these long-term damages, informing the policy makers of the plausible mechanisms for alleviating the losses. In addition, our



study shows that considering anthropogenic changes in extreme events may be of particular importance when measuring the impact of climate change.

Table 4: Twenty-Year Impact of Low-Probability Adverse Precipitation Shocks on Household Wages

	Urban Parameter (Std. Err.)	Rural Parameter (Std. Err.)	All Parameter (Std. Err.)
Dummy variable for at least one year in the first percentile			
1 to 5 years ago	-0.364*** (0.034)	-0.137*** (0.028)	-0.302*** (0.022)
6 to 10 years ago	-0.045*** (0.017)	-0.160*** (0.021)	-0.103*** (0.014)
11 to 15 years ago	0.061*** (0.017)	0.128*** (0.026)	0.153*** (0.015)
16 to 20 years ago	-0.258*** (0.052)	0.037 (0.041)	-0.146*** (0.032)
R-squared	0.22	0.31	0.28
Precipitation dummy variables=0	38.94***	23.14***	88.93***
State Fixed Effects=0	366.10***	393.12***	890.90***
All variables=0	512.14***	432.32***	1066.60***
Observations	98314	45313	143627

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

Table 5: Ten-Year Impact of Low-Probability Adverse Precipitation Shocks on Household Wages

	Urban Parameter (Std. Err.)	Rural Parameter (Std. Err.)	All Parameter (Std. Err.)
<b>Dummy variable for first percentile</b>			
1 year ago	-0.687*** (0.142)	-0.295** (0.013)	-0.447*** (0.098)
2 years ago	-0.329*** (0.043)	-0.070*** (0.029)	-0.277*** (0.024)
3 years ago	0.004 (0.124)	---	0.123 (0.125)
4 years ago	0.173 (0.113)	---	0.285*** (0.112)
5 years ago	-0.188** (0.081)	-0.063 (0.073)	-0.108** (0.055)
6 years ago	-0.181** (0.090)	---	-0.040 (0.091)
7 years ago	0.043* (0.024)	-0.179*** (0.033)	-0.023 (0.021)
8 years ago	-0.223*** (0.028)	0.116* (0.061)	-0.215*** (0.025)
9 years ago	-0.331*** (0.048)	-0.360*** (0.052)	-0.557*** (0.039)
10 years ago	0.125*** (0.025)	-0.091*** (0.030)	0.070*** (0.021)
R-squared	0.22	0.31	0.28
Precipitation dummy variables=0	33.00***	15.52***	56.74***
State Fixed Effects=0	362.73***	382.90***	883.43***
All variables=0	452.73***	404.66***	940.04***
Observations	98314	45313	143627

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

Table 6: Twenty-Year Impact of Low-Probability Adverse Precipitation Shocks on Household Wages Accounting for Sample Selectivity

	Urban Parameter (Std. Err.)	Rural Parameter (Std. Err.)	All Parameter (Std. Err.)
Dummy variable for at least one year in the first percentile			
1 to 5 years ago	-0.365*** (0.034)	-0.138*** (0.028)	-0.304*** (0.022)
6 to 10 years ago	-0.046*** (0.017)	-0.159*** (0.021)	-0.103*** (0.014)
11 to 15 years ago	0.062*** (0.017)	0.127*** (0.026)	0.154*** (0.015)
16 to 20 years ago	-0.258*** (0.052)	0.039 (0.041)	-0.146*** (0.032)
Sigma	0.913 (0.003)	0.899 (0.004)	0.942 (0.002)
Rho	-0.217 (0.015)	-0.260 (0.019)	-0.203 (0.013)
Precipitation dummy variables=0	39.15***	23.21***	89.47***
State Fixed Effects=0	365.67***	391.69***	891.41***
All variables=0	546.71***	429.41***	1097.43***
Observations	111511	51927	163438

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

5 The selection equation of the Heckman model included the following variables: a constant, head of household's age, and head of household's age squared, three dummy variables indicating whether the household had at least one person receiving a pension, remittances, or dividends from an investment. All six coefficients were significant at the five percent critical level. The head of household's age, dividends dummy variable and constant parameters have positive signs. The head of household's age squared, and pension and remittance dummy parameters have negative signs.

Table 7: Ten-Year Impact of Low-Probability Adverse Precipitation Shocks on Household Wages Accounting for Sample Selectivity

	Urban Parameter (Std. Err.)	Rural Parameter (Std. Err.)	All Parameter (Std. Err.)
<b>Dummy variable for first percentile</b>			
1 year ago	-0.692*** (0.141)	-0.294** (0.130)	-0.448*** (0.097)
2 years ago	-0.331*** (0.043)	-0.071*** (0.029)	-0.279*** (0.024)
3 years ago	0.007 (0.125)	---	0.126 (0.125)
4 years ago	0.174 (0.113)	---	0.287*** (0.113)
5 years ago	-0.187** (0.081)	-0.062 (0.073)	-0.107** (0.055)
6 years ago	-0.185** (0.090)	---	-0.043 (0.091)
7 years ago	0.043* (0.024)	-0.180*** (0.033)	-0.023 (0.021)
8 years ago	-0.224*** (0.028)	0.118* (0.061)	-0.216*** (0.025)
9 years ago	-0.329*** (0.048)	-0.355*** (0.052)	-0.555*** (0.039)
10 years ago	0.126*** (0.025)	-0.092*** (0.030)	0.070*** (0.021)
Sigma	0.914 (0.003)	0.899 (0.004)	0.942 (0.002)
Rho	-0.218 (0.015)	-0.259 (0.020)	-0.202 (0.013)
Precipitation dummy variables=0	33.35***	15.47***	57.03***
State Fixed Effects=0	362.25***	381.74***	883.97***
All variables=0	485.57***	402.99***	971.53***
Observations	111511	51927	163438

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

5 The selection equation of the Heckman model included the following variables: a constant, head of household's age, and head of household's age squared, three dummy variables indicating whether the household had at least one person receiving a pension, remittances, or dividends from an investment. All six coefficients were significant at the five percent critical level. The head of household's age, dividends dummy variable and constant parameters have positive signs. The head of household's squared, and pension and remittance dummy parameters have negative signs.

Table 8: Twenty-Year Impact of Low-Probability Adverse Precipitation Shocks on Household Wages by Wealth

	At least one year over 5-year time frame had precipitation level in first percentile			
	1 to 5 years ago	6 to 10 years ago	11 to 15 years ago	16 to 20 years ago
	Parameter (Std. Err.)	Parameter (Std. Err.)	Parameter (Std. Err.)	Parameter (Std. Err.)
Urban-Low 25%	-0.138*** (0.031)	0.005 (0.020)	-0.004 (0.021)	-0.221*** (0.070)
Urban-Mid 50%	-0.065*** (0.019)	-0.021** (0.010)	0.023** (0.010)	-0.026 (0.030)
Urban-Top 25%	-0.065 (0.057)	-0.049*** (0.019)	0.032 (0.021)	-0.106** (0.053)
Rural-Low 25%	-0.077*** (0.027)	0.027** (0.027)	0.146*** (0.026)	0.049 (0.048)
Rural-Mid 50%	-0.034** (0.016)	-0.022* (0.015)	0.003 (0.015)	-0.004 (0.023)
Rural-Top 25%	0.033 (0.047)	-0.032 (0.025)	0.022 (0.033)	-0.011 (0.056)
All-Low 25 %	-0.107*** (0.016)	-0.048*** (0.016)	0.060*** (0.016)	-0.014 (0.034)
All-Mid 50%	-0.036*** (0.014)	-0.036*** (0.008)	0.049*** (0.009)	-0.059*** (0.019)
All-Top 25 %	-0.025 (0.039)	-0.032 (0.015)	0.042*** (0.017)	-0.064* (0.039)

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

Table 9: Ten-Year Impact of Low-Probability Adverse Precipitation Shocks on Household Wages by Wealth

	Urban Low 25% Parameter (Std. Err.)	Urban Middle 50% Parameter (Std. Err.)	Urban Top 25% Parameter (Std. Err.)	Rural Low 25% Parameter (Std. Err.)	Rural Middle 50% Parameter (Std. Err.)	Rural Top 25% Parameter (Std. Err.)
Dummy variable for first percentile						
1 year ago	-0.296** (0.123)	-0.218*** (0.071)	0.153 (0.0186)	-0.004 (0.091)	-0.096 (0.079)	0.021 (0.0175)
2 years ago	-0.152*** (0.036)	-0.041* (0.024)	-0.138* (0.080)	-0.045* (0.027)	-0.035** (0.016)	0.010 (0.045)
3 years ago	0.139 (0.112)	-2.610×10 <sup>-5</sup> (0.064)	0.183 (0.151)	--- ---	--- ---	--- ---
4 years ago	0.105 (0.271)	-0.048 (0.063)	0.024 (0.100)	--- ---	--- ---	--- ---
5 years ago	-0.037 (0.067)	-0.085* (0.048)	-0.040 (0.201)	0.018 (0.062)	0.017 (0.045)	0.103 (0.117)
6 years ago	-0.032 (0.052)	-0.074 (0.054)	0.005 (0.092)	--- ---	--- ---	--- ---
7 years ago	0.089*** (0.028)	-0.010 (0.014)	-0.028 (0.025)	0.053 (0.045)	-0.031* (0.018)	-0.039 (0.035)
8 years ago	-0.086** (0.043)	-0.021 (0.017)	-0.170*** (0.034)	-0.0148 (0.118)	0.051 (0.036)	0.028 (0.072)
9 years ago	-0.036 (0.047)	-0.083*** (0.031)	-0.058 (0.071)	-0.201*** (0.044)	-0.049 (0.035)	-0.043 (0.080)
10 years ago	0.009 (0.032)	0.001 (0.014)	0.021 (0.026)	0.091** (0.046)	-0.022 (0.018)	-0.021 (0.036)
R-squared	0.11	0.11	0.02	0.12	0.13	0.05
Precipitation dummy variables=0	5.92***	6.12***	3.66***	4.21***	2.21**	0.54
State Fixed Effects=0	37.15***	62.31***	4.64***	37.97***	46.57***	5.78***
All variables=0	48.16***	102.24***	13.92***	28.87***	70.16***	13.34***
Observations	24579	49363	24372	11638	22347	11328

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

Table 10: Ten-Year Impact of Low-Probability Adverse Precipitation Shocks on Household Wages by Wealth

	All Low 25% Parameter (Std. Err.)	All Middle 50% Parameter (Std. Err.)	All Top 25% Parameter (Std. Err.)
Dummy variable for first percentile			
1 year ago	-0.125 (0.079)	-0.187*** (0.066)	-0.108 (0.166)
2 years ago	-0.091*** (0.020)	-0.022 (0.016)	-0.025 (0.048)
3 years ago	0.179 (0.144)	-0.018 (0.065)	0.112 (0.146)
4 years ago	-0.257 (0.426)	0.010 (0.061)	0.047 (0.099)
5 years ago	-0.023 (0.046)	-0.036 (0.033)	-0.045 (0.115)
6 years ago	0.068 (0.050)	-0.061 (0.033)	-0.034 (0.086)
7 years ago	0.045* (0.026)	-0.043*** (0.012)	-0.012 (0.020)
8 years ago	-0.075* (0.044)	-0.024 (0.016)	-0.165*** (0.029)
9 years ago	-0.274*** (0.038)	-0.063*** (0.025)	-0.118** (0.054)
10 years ago	0.055** (0.023)	-0.008 (0.011)	0.049** (0.021)
R-squared	0.14	0.09	0.03
Precipitation dummy variables=0	10.27***	4.57***	4.82***
State Fixed Effects=0	116.40***	119.04***	8.65***
All variables=0	89.28***	115.48***	18.61***
Observations	39327	69694	34606

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.



Table 11: Twenty-Year Impact of the Number of Standard Deviations Below the Precipitation Mean on Household Wages

	Urban Parameter (Std. Err.)	Rural Parameter (Std. Err.)	All Parameter (Std. Err.)
<b>Standard deviations below the mean</b>			
Average over 1 to 5 years ago	-0.157*** (0.027)	-0.356*** (0.028)	-0.402*** (0.019)
Average over 6 to 10 years ago	-0.135*** (0.034)	-0.439*** (0.035)	-0.394*** (0.024)
Average over 11 to 15 years ago	0.107*** (0.027)	-0.035 (0.027)	0.153*** (0.019)
Average over 16 to 20 years ago	0.179*** (0.031)	-0.215*** (0.033)	0.110*** (0.023)
R-squared	0.21	0.31	0.28
Precipitation variables=0	30.51***	84.38***	230.19***
State Fixed Effects=0	198.81***	325.96***	520.34***
All variables=0	511.75***	444.51***	1085.35***
Observations	98314	45313	143627

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

Table 12: Ten-Year Impact of the Number of Standard Deviations Below the Precipitation Mean on Household Wages

	Urban Parameter (Std. Err.)	Rural Parameter (Std. Err.)	All Parameter (Std. Err.)
Standard deviations below the mean			
1 year ago	-0.051*** (0.015)	-0.042*** (0.016)	-0.108*** (0.011)
2 years ago	-0.109*** (0.010)	-0.090*** (0.011)	-0.132*** (0.007)
3 years ago	0.041*** (0.014)	-1.837×10 <sup>-4</sup> (0.015)	0.082*** (0.010)
4 years ago	-0.025*** (0.015)	-0.229*** (0.016)	-0.168*** (0.011)
5 years ago	-0.104** (0.013)	-0.054*** (0.012)	-0.118*** (0.009)
6 years ago	-0.177*** (0.015)	-0.097*** (0.018)	-0.174*** (0.011)
7 years ago	-0.028** (0.013)	-0.117*** (0.013)	-0.115*** (0.009)
8 years ago	-0.076*** (0.010)	0.005 (0.013)	-0.083*** (0.008)
9 years ago	-0.099*** (0.013)	-0.150*** (0.014)	-0.103*** (0.009)
10 years ago	-0.007 (0.012)	-0.084*** (0.011)	-0.109*** (0.008)
R-squared	0.22	0.32	0.28
Precipitation variables=0	40.72***	52.14***	159.10***
State Fixed Effects=0	138.22***	188.51***	369.48***
All variables=0	456.15***	397.11***	968.74***
Observations	98314	45313	143627

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

Table 13: Twenty-Year Impact of the Number of Standard Deviations Below the Precipitation Mean on Household Wages Accounting for Sample Selectivity

	Urban Parameter (Std. Err.)	Rural Parameter (Std. Err.)	All Parameter (Std. Err.)
<b>Standard deviations below the mean</b>			
Average over 1 to 5 years ago	-0.155*** (0.027)	-0.354*** (0.028)	-0.401*** (0.019)
Average over 6 to 10 years ago	-0.135*** (0.034)	-0.440*** (0.035)	-0.395*** (0.024)
Average over 11 to 15 years ago	0.106*** (0.027)	-0.035 (0.027)	0.152*** (0.019)
Average over 16 to 20 years ago	0.180*** (0.031)	-0.212*** (0.033)	0.112*** (0.023)
Sigma	0.914 (0.003)	0.896 (0.004)	0.940 (0.002)
Rho	-0.217 (0.015)	-0.257 (0.020)	-0.203 (0.013)
Precipitation variables=0	30.49***	83.78***	230.65***
State Fixed Effects=0	198.86***	324.75***	520.49***
All variables=0	500.79***	419.29***	1047.15***
Observations	111511	51927	163438

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

5 The selection equation of the Heckman model included the following variables: a constant, head of household's age, and head of household's age squared, three dummy variables indicating whether the household had at least one person receiving a pension, remittances, or dividends from an investment. All six coefficients were significant at the five percent critical level. The head of household's age, dividends dummy variable and constant parameters have positive signs. The head of household's age squared, and pension and remittance dummy parameters have negative signs.

Table 14: Ten-Year Impact of the Number of Standard Deviations Below the Precipitation Mean on Household Wages Accounting for Sample Selectivity

	Urban Parameter (Std. Err.)	Rural Parameter (Std. Err.)	All Parameter (Std. Err.)
Standard deviations below the mean			
1 year ago	-0.050*** (0.015)	-0.042*** (0.016)	-0.107*** (0.011)
2 years ago	-0.109*** (0.010)	-0.090*** (0.011)	-0.132*** (0.007)
3 years ago	0.040*** (0.014)	$-3.920 \times 10^{-5}$ (0.015)	0.082*** (0.010)
4 years ago	-0.026* (0.016)	-0.230*** (0.016)	-0.168*** (0.011)
5 years ago	-0.104*** (0.013)	-0.053*** (0.012)	-0.118*** (0.009)
6 years ago	-0.177*** (0.015)	-0.097*** (0.018)	-0.0175*** (0.011)
7 years ago	-0.029** (0.013)	-0.0117*** (0.013)	-0.115*** (0.009)
8 years ago	-0.075*** (0.010)	0.006 (0.013)	-0.083*** (0.008)
9 years ago	-0.099*** (0.013)	-0.151*** (0.014)	-0.104*** (0.009)
10 years ago	-0.007 (0.012)	-0.084*** (0.011)	-0.109*** (0.008)
Sigma	0.913 (0.003)	0.894 (0.004)	0.938 (0.002)
Rho	-0.217 (0.015)	-0.258 (0.019)	-0.205 (0.013)
Precipitation variables=0	40.81***	52.19***	159.69***
State Fixed Effects=0	138.29***	187.95***	369.79***
All variables=0	446.63***	375.49***	936.15***
Observations	111511	51927	163438

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

5 The selection equation of the Heckman model included the following variables: a constant, head of household's age, and head of household's age squared, three dummy variables indicating whether the household had at least one person receiving a pension, remittances, or dividends from an investment. All six coefficients were significant at the five percent critical level. The head of household's age, dividends dummy variable and constant parameters have positive signs. The head of household's squared, and pension and remittance dummy parameters have negative signs.

Table 15: Twenty-Year Impact of the Number of Standard Deviations Below the Precipitation Mean on Household Wages by Wealth

	SDs below the mean (Average over 5-year time frame)			
	1 to 5 years ago	6 to 10 years ago	11 to 15 years ago	16 to 20 years ago
	Parameter (Std. Err.)	Parameter (Std. Err.)	Parameter (Std. Err.)	Parameter (Std. Err.)
Urban-Low 25%	-0.060** (0.029)	-0.063* (0.038)	0.200*** (0.030)	0.090*** (0.034)
Urban-Mid 50%	-0.018 (0.015)	-0.023 (0.019)	-0.023 (0.015)	0.031* (0.017)
Urban-Top 25%	-0.081*** (0.032)	0.071* (0.040)	0.116*** (0.033)	0.109*** (0.039)
Rural-Low 25%	-0.171*** (0.035)	-0.078* (0.046)	-0.034 (0.036)	0.030 (0.043)
Rural-Mid 50%	-0.095*** (0.016)	-0.068*** (0.020)	0.023 (0.015)	-0.031* (0.018)
Rural-Top 25%	-0.084** (0.037)	-0.158*** (0.044)	-0.034 (0.034)	-0.113*** (0.041)
All-Low 25 %	-0.0139*** (0.020)	-0.091*** (0.027)	0.080*** (0.022)	-0.007 (0.025)
All-Mid 50%	-0.093*** (0.011)	-0.086*** (0.014)	0.022** (0.011)	0.037*** (0.013)
All-Top 25 %	-0.118*** (0.025)	0.013 (0.031)	0.090*** (0.025)	0.051* (0.029)

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

Table 16: Ten-Year Impact of the Number of Standard Deviations Below the Precipitation Mean on Household Wages by Wealth

	Urban Low 25% Parameter (Std. Err.)	Urban Middle 50% Parameter (Std. Err.)	Urban Top 25% Parameter (Std. Err.)	Rural Low 25% Parameter (Std. Err.)	Rural Middle 50% Parameter (Std. Err.)	Rural Top 25% Parameter (Std. Err.)
SDs below the mean						
1 year ago	-0.042** (0.018)	-0.001 (0.008)	0.005 (0.017)	0.070 (0.022)	-0.007 (0.009)	-0.009 (0.019)
2 years ago	-0.039*** (0.011)	-0.010* (0.006)	-0.049*** (0.013)	-0.028** (0.013)	-0.027*** (0.006)	0.013 (0.015)
3 years ago	0.019 (0.017)	-0.002 (0.008)	0.072*** (0.016)	0.010 (0.020)	-0.007 (0.009)	-0.008 (0.019)
4 years ago	-0.019 (0.018)	-0.006 (0.009)	0.004 (0.017)	-0.137*** (0.022)	-0.059*** (0.009)	-0.044** (0.019)
5 years ago	-0.028** (0.014)	-0.016** (0.007)	-0.090*** (0.017)	-0.087*** (0.015)	-0.006 (0.007)	0.009 (0.017)
6 years ago	-0.046*** (0.016)	-0.044*** (0.008)	0.010 (0.017)	0.049** (0.025)	-0.045*** (0.010)	-0.058*** (0.023)
7 years ago	-0.029** (0.015)	0.007 (0.007)	0.015 (0.015)	-0.025 (0.021)	-0.021*** (0.008)	-0.008 (0.015)
8 years ago	-0.019 (0.012)	-0.016*** (0.006)	-0.039*** (0.012)	-0.023 (0.018)	0.003 (0.007)	-0.041*** (0.016)
9 years ago	-0.048*** (0.013)	-0.018*** (0.007)	0.006 (0.015)	-0.080*** (0.017)	-0.028*** (0.008)	-0.051*** (0.019)
10 years ago	-0.061*** (0.013)	0.020*** (0.007)	-0.012 (0.014)	0.007 (0.013)	-0.011* (0.006)	-0.001 (0.014)
R-squared	0.11	0.11	0.03	0.12	0.14	0.06
Precipitation variables=0	7.09***	6.20***	6.03***	10.22***	9.98***	2.35***
State Fixed Effects=0	15.17***	22.68***	4.88***	24.25***	23.58***	4.52***
All variables=0	48.16***	106.16***	12.81***	27.56***	67.43***	13.03***
Observations	24579	49363	24372	11638	22347	11328

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions.

In all rural regressions, the federal district is also excluded as there are no rural municipios in that state. In the rural regressions with the low-income 25% households the Roraima dummy variable is excluded.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. Parameter and standard error estimates are available upon request.

Table 17: Ten-Year Impact of the Number of Standard Deviations Below the Precipitation Mean on Household Wages by Wealth

	All Low 25% Parameter (Std. Err.)	All Middle 50% Parameter (Std. Err.)	All Top 25% Parameter (Std. Err.)
SDs below the mean			
1 year ago	-0.028** (0.013)	-0.018*** (0.006)	-0.010 (0.013)
2 years ago	-0.041*** (0.008)	-0.019*** (0.004)	-0.029*** (0.010)
3 years ago	0.049*** (0.012)	0.010* (0.006)	0.048*** (0.013)
4 years ago	-0.086*** (0.013)	-0.051*** (0.006)	-0.003 (0.013)
5 years ago	-0.042*** (0.009)	-0.031*** (0.005)	-0.072*** (0.012)
6 years ago	-0.004 (0.012)	-0.053*** (0.006)	-0.010 (0.014)
7 years ago	-0.017* (0.011)	-0.021*** (0.005)	0.014 (0.011)
8 years ago	-0.012 (0.009)	-0.020*** (0.004)	-0.045*** (0.009)
9 years ago	-0.043*** (0.010)	-0.016*** (0.005)	-0.002 (0.012)
10 years ago	-0.040*** (0.008)	-0.018*** (0.005)	-0.013 (0.011)
R-squared	0.14	0.09	0.03
Precipitation variables=0	16.31***	24.88***	7.64***
State Fixed Effects=0	59.01***	49.99***	7.94***
All variables=0	89.29***	121.38***	19.43***
Observations	39327	69694	34606

1 \*\*\*, \*\*, and \* indicate parameter significance at the 1, 5, and 10 percent critical error

2 Estimates are made using PNAD household sampling weights.

3 All specifications include state fixed effects. The state fixed effect for Sao Paulo is excluded in all of the regressions. In the rural regressions, the federal district is also excluded as there are no rural municipalities in that state.

4 Additional household variables were included in the regression: a 1992 dummy variable, the head of household's age and age squared, the number of household members by age category (15-25, 36-45, 46-55, greater than 55), and the number of household members by age category squared. All household variable parameters are significant at the five percent critical level with the exception of the number of household members in the 36 to 45 age category squared.

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