Drought in the City:
The Economic Impact of Water Scarcity in Latin American Metropolitan Areas

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Abstract

While the harmful impact of droughts in rural areas is a well-documented topic, how urban areas are impacted by water scarcity remains largely an open question. In this paper, we provide evidence that cities' economies also significantly suffer from droughts. If the public debate focuses on the repercussions of excess rainfall on cities, our results even suggest that the impact of droughts is larger than the impact of wet events. We draw this conclusion by compiling monthly labor force surveys covering 13,000,000 workers from 78 of the largest metropolitan areas of Latin America over 10 years, and by analyzing the impact of exogenous rainfall variations on workers and on firms. We show that large sustained dry events decrease the probability of employment, wages, the number of hours worked and incomes. Informal workers suffer the most. We show that a worsening of health conditions and an increase in power outages are two pathways explaining our results.

Key words: Droughts, Labor Markets, Urban Economics, Latin America

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You take delight not in a city's seven or seventy wonders but in the answer it gives to a question of yours.

— Italo Calvino, Invisible Cities

1 Introduction

Urban growth is a thirsty business. The increase in urban inhabitants from 54 percent in 2014 to an estimated 66 percent by 2050 (UN-ESA 2014) is projected to increase the demand for water from cities by 50 to 70 percent (McKinsey 2009). Yet, one fourth of cities around the world are already water-stressed and exposed to perennial water shortages (McDonald, Weber, et al. 2014).[1] With climate and land use change, even river basins with important reserves of freshwater, such as in São Paulo, have experienced major droughts over the last years, leading to water shortages. To what extent water availability matters for economic activity in urban settings remains largely unknown. The Intergovernmental Panel on Climate Change (IPCC) emphasizes the negative impact of floods in cities, but does not address the potential risk associated with droughts. We highlight in this paper that droughts can significantly harm the economic activity of large metropolitan areas. Our results even suggest that the magnitude of the impact of droughts on labor market outcomes is larger than the impact of wet shocks, like those that cause floods.

There are several reasons to expect such a large negative impact of droughts on cities' economies. Water is one of the principal inputs to generate electricity (Fthenakis and Kim 2010), even when the technology used is not hydropower. Consequently, water scarcity can lead to electric shutdowns as was recently seen in India or in São Paulo.[2] In addition, health literature points out the negative effects of droughts on health conditions as droughts increase the risk of diarrhea, infections and the survival rate of vectors of diseases (Kovats et al. 2003). Cities' higher population density favors the spread of diseases compared to rural areas, particularly in the absence of adequate sanitation and sewerage. This deterioration of health can have direct consequences for labor productivity.

Our paper focuses on Latin America, the second most urbanized region of the world after North America (82 percent *vs* 80 percent, UN-ESA 2014). Our research uses monthly microeconomic labor market data from 78 of the largest cities on the continent between 2005 and 2014. We merge them with global gridded weather data from 1900 to 2014, allowing us to construct exogenous indexes of droughts based on abnormal deviations from long term means of rainfall. In this natural experiment setting, we show that large and sustained dry shocks (droughts) negatively impact economic activity. During droughts, the probability of an active worker to be employed decreases, as well as the number of hours worked, the wages and the labor incomes of informal occupied workers. Our results are robust to several specifications. They also hold when using different datasets (household surveys, administrative data on the universe of formal Brazilian firms, Enterprise Surveys data), all covering different cities and different periods of time. What mechanisms drive this result? In our study, we highlight that droughts in Latin America significantly increase power outages. Using a panel of hospital admissions data from Brazil, we also find a worsening of health conditions when droughts occur.

In addition, our empirical model allows us to compare directly the impact of droughts with the impact of similar wet shocks, including wet shocks of an intensity that can cause floods. Compared

1. McDonald, Green, et al. (2011) modeled results show that currently 150 million people live in cities with perennial water shortage, defined as having less than 100L per person per day of sustainable surface and groundwater flow within their urban extent. By 2050, demographic growth will increase this figure to almost 1 billion people. They predict that climate change will cause water shortage for an additional 100 million urbanites.

2. See: `http://www.wri.org/blog/2015/06/global-tour-7-recent-droughts` and `http://www.theguardian.com/world/2015/jan/23/brazil-worst-drought-history`

to droughts, we do not find that large wet deviations cause a general decrease in employment. Also, when large repeated dry shocks decrease monthly labor incomes by eight percent, similar wet shocks decrease monthly incomes by two to four percent. While floods tend to attract most of the media attention (Eisensee and Strömberg 2007), our paper emphasizes the importance for cities to protect themselves from droughts.

Our results are striking as Latin America has the highest infrastructure density among developing regions, in spite of its own infrastructure gap. [3] In a recent working paper, Ashraf et al. (2017) find that water outages in the city of Lusaka, Zambia, negatively affect health outcomes and reduce the quantity of financial transactions. Arguably, the quantity and quality of infrastructure in Latin America is better than in less developed countries such as Zambia. Yet, our results show that the problem of water in cities is true for middle incomes countries, and not only in low-incomes countries. Our results also show that the negative economic impact of water scarcity is true at a large geographic scale (one region compared to one city).

The remainder of the paper is organized as follows. Section 2 presents the literature. Section 3 describes the data and the empirical strategy. Section 4 presents our results on the impact of shocks and section 5 analyzes pathways. Section 6 discusses the findings and concludes.

2 Prior research

An important literature analyzes the impact of positive and negative rainfall shocks on agricultural activity. It shows that even shocks of a small magnitude have important consequences on yields. Droughts then translate into increases in poverty and decreases of key development outcomes such as health and education in developing countries (Kazianga and Udry 2006; Dercon 2004; Hallegatte et al. 2016). For example, it has been shown that rainfall variability impacts agricultural wages in Bengladesh (Mueller and Quisumbing 2011), gender wage gap in rural India (Mahajan 2017), land invasions in Brazil (Hidalgo et al. 2010), local tax revenues in Mali (Sanoh 2015), farmers' stress level in Kenya (Chemin, De Laat, and Haushofer 2013 in Kenya), or violence towards women in India (Sekhri and Storeygard 2014).

In comparison, the literature on rainfall shocks in urban areas is more limited. At the city level, looking at 1,800 cities between 2003 and 2008, Kocornik-Mina et al. (2015) show that large scale floods (i.e. those displacing more than 100,000 people) reduce night-time lights (NTL) by two to eight percent within cities the year of the flood, but that even hard-hit cities recover within one year. Acevedo (2015) finds similar results on the impact of floods and on the speed of recovery using microeconomic data on labor markets outcomes in the Colombian Carribean. For dry shocks, existing research has shown an indirect effect of drougths on cities. Rural-urban migration increases with droughts as in Africa (Henderson, Storeygard, and Deichmann 2017), in Brazil (Bastos, Busso, and Miller 2013) and recently in Syria (Kelley et al. 2015). Urban centers are then affected by droughts in the long term due to an accelerated sector reallocation. A rich litterature show that droughts increase the probability of conflicts (Miguel, Satyanath, and Sergenti 2004; Couttenier and Soubeyran 2014). Almer, Laurent-Lucchetti, and Oechslin (2017) show that the relationship is particularly true in areas close from cities. Again, one might then expect consequences of these conflicts on labor market outcomes.

The literature highlighting a direct economic impact of water scarcity on cities is thin. The closest paper from ours is the working paper by Ashraf et al. (2017) mentioned above. The authors study the impact of water outages in Lusaka, Zambia. They demonstrate that water outages increase the incidence of diseases (diarrhea, upper respiratory infections, typhoid fever and measle), which

3. Fay et al. (2017) notes that some 17 percent of Latin Americans have no access to a private, improved sanitation facility and one-fifth of them still practice open defecation. Additionally, only about a third of wastewater is treated.

translate into a reduction of money-banking transactions and into an increase in the time that girls spend at their chores. If our conclusions converge with Ashraf et al. (2017), the two papers differ in several ways. When Ashraf et al. (2017) tests the impact of water outages using data from the main service provider of water, our paper uses rainfall data. Our paper also adds at least three insights to Ashraf et al. (2017)'s findings. First, we show that not only money banking is impacted but labor market more globally. Second, we add a second pathway to explain the results. We demonstrate that power outages for firms increase with droughts. Third, while Ashraf et al. (2017) highlight an impact of droughts in a city with poor infrastructures from one of the least advanced economy on the planet, we show convergent results for cities richer in infrastructures from middle income countries. Hence, our findings suggest that a broad range of countries can suffer from droughts. Our paper is also related to Mueller and Osgood (2009). The authors find a negative impact of negative shocks on wages in rural Brazil using survey data between 1992 and 1995. They are however unable to confirm a direct impact of droughts on wages in urban areas, contrary to our findings.

Our paper also relates to the Climate-Economy Literature (Hsiang 2010; Hsiang 2016; Carleton and Hsiang 2016) that has more recently pushed towards the exploration of the role of temperature as a proxy for climate variations (Dell, Jones, and Olken 2012; Graff Zivin and Neidell 2014; Burke, Hsiang, and Miguel 2015). In particular, Graff Zivin and Neidell (2014) use US daily temperature and individual data from the 2003-06 National Time Use Surveys to show that positive temperature shocks lead to substantial changes in labor supply. Those results echo those found at the macroeconomic level where patterns of responses to variation in temperatures are consistent with labor effects (Hsiang 2010; Deryugina and Hsiang 2014; Burke, Hsiang, and Miguel 2015).

Finally, our approach is connected to the literature on large natural disasters. This literature finds mixed impacts of shocks on labor market. In Indonesia, Kirchberger (2017) finds labor markets to be rather resilient to earthquakes and even a positive impact on wages for agricultural workers, driven by a labor supply reallocation towards the construction sector. Those findings echo those of Belasen and Polachek (2008) and Belasen and Polachek (2009) who look at the impact of hurricanes on labor markets in Florida and identify a positive impact on wage but a slower growth in employment in counties directly hit compared. In Guatemala, Baez et al. (2016), look at the impact of tropical storm Agatha (2010). They find that households in urban areas bore the brunt of the burden with their per capita expenditure falling by over eight percent.

3 Methods

3.1 Main datasets

The main result of our paper are obtained by combining two sets of data: micro data on labor market outcomes and gridded weather data. Data on labor market outcomes come from the Labor Database for Latin America and The Caribbean (LABLAC) initiative. LABLAC is a joint project conducted by the Center for Distributional, Labor and Social Studies (CEDLAS) at the University of La Plata (Argentina) and the World Bank. It aims to harmonize the different labor force surveys conducted in the region. It includes information from over 300 labor surveys carried out in 24 Latin America and Caribbean countries since 2005.

We construct our dataset by focusing on all the rounds of surveys that are representative at the metropolitan area level. Our combined repeated cross-section dataset covers around 13 million active individuals living in 78 metropolitan areas from nine countries (Brazil, Chile, Colombia, El Salvador, Ecuador, Mexico, Paraguay, Peru, and Uruguay). We track information on their employment status (whether they are occupied or not), on the number of hours they worked, and on their hourly wages. Our dataset is monthly and covers the full period between 2005 and 2014 for most countries. Our sample is representative of a population of about 300 million active people living in the biggest cities from these nine countries, that is about half of the total Latin America population. Table A1 in appendix summarizes the different rounds of surveys used in this study.

Rainfall data come from the University of Delaware's Global Land Temperature and Precipitation Data (Willmott, Matsuura, and Legates 2001). This gridded dataset contains monthly observations of precipitations (in mm) and of average temperatures (in C) at the 0.5 degree gridcell level (approximately 50km at the equator) from 1900 to 2014. We merge the weather data and LABLAC using the centroid of each sampled metropolitan area.

3.2 Empirical Strategy

We aim to measure the impact of droughts on labor market outcomes. In this subsection, we explain how we measure droughts and we present the empirical model.

3.2.1 Droughts

The Oxford dictionary defines droughts as "prolonged periods of abnormally low rainfall, leading to a shortage of water". [4] They are the combination of two dimensions: an abnormal level and a time dimension.

The literature often considers a level of rainfall as abnormal when it lies one standard deviation below the long term average observed in the area. We follow this approach. However, if most papers use annual data, our paper use monthly data, and if annual rainfall one standard deviations below the long term average of rainfall can lead to shortages of water, it is unlikely that only one month of negative deviation in rainfall will deplete available water resources and cause a drought.

As a consequence, we proceed in two ways to define droughts using monthly data. First, we define two levels of abnormality for rainfall. We define as small shocks variations of rainfall between one and two standard deviations from the average of rainfall between 1900-2014. We define as large shocks deviations of rainfall larger than two standard deviations from the long term average. Second, shocks need to be sustained over a prolonged period of time to cause a drought. We construct droughts variables by counting the number of consecutive months during which levels of rainfall are abnormal. We start by looking at the impact of shocks of a length up to two months - a number that allows us to have sufficient observations for large shocks.Calling $S^k_{j,m}$ a rainfall shock of intensity $k = 1,2$ in city j during month m, our variable $Drought^k_{j,m}$ is such that

$$Drought^{k=1,2}_{j,m} = \begin{cases} 0 & \text{if } S^k_{j,m} = 0 \,\&\, S^k_{j,m-1} = 0 \\ 1 & \text{if } S^k_{j,m} = 1 \,\&\, S^k_{j,m-1} = 0 \\ 2 & \text{if } S^k_{j,m} = 1 \,\&\, S^k_{j,m-1} = 1 \end{cases}$$

Where $k = 1$ refers to small shocks and $k = 2$ refers to large shocks. m does not stand for the 12 calendar months but represents each of the 120 months covered by our study. As a robustness, we define only one threshold for shocks and extend the period for up to four months. Our empirical approach presents different advantages. First, we could have used level of rainfalls instead of deviation of rainfall to study the impact of water availability. However, we know that population dynamics and urbanization have historical origins born out of deliberate choices to establish cities in locations where climate is the most favorable to economic activity. This means that current levels of economic activity and levels of rainfall are potentially endogenous. Using local random month-to-month deviations

4. See: https://en.oxforddictionaries.com/definition/drought

of rainfall allows to overcome this issue and obtain causal results on water availability. Second, measuring droughts using rainfall data allows to construct wet shocks symmetric to dry shocks. In a unique framework, we can then compare directly the economic consequences of droughts to the economic consequences of wet spells, including wet spells large enough to cause floods. Hence, we construct small and large wet shocks symmetric to dry shocks, knowing that large wet spells correspond to the kind of rainfall shocks that would be expected to result in floods and landslides. [5]

3.2.2 Equation

To estimate the effect of droughts on labor market outcomes, our baseline model is:

$$\begin{aligned} Labor\,Outcome_{i,j,m} &= \beta Drought^{k}_{j,m} + \tau_1 Temperature_{j,m} \\ &\quad + \tau_2 Temperature_{j,m-1} + \eta_{j,y} + \chi_m + \epsilon_{i,j,m,y} \text{ for } k = 1,2 \qquad (1) \end{aligned}$$

where $Labor\,Outcome_{i,j,m}$ is the labor market outcome for individual i living in city j during month m. This labor market outcome can be whether the individual is employed or not, the logarithm of her/his hourly wage expressed in 2005 PPP, the logarithm of the number of hours worked during the month and the logarithm of her/his monthly labor income. We control for temperatures (in C). This matters as rainfall, temperatures and economic activity are correlated (Auffhammer et al. 2013; Hsiang 2010; Dell, Jones, and Olken 2012). We include city by year fixed effects to control for time-invariant city-specific characteristics during the year ($\eta_{j,y}$). Month by year fixed effects control for monthly variations common to the region (χ_m). We cluster standard errors at the city level to respect the quasi-experimental design of the study (Abadie et al. 2017). Our estimation strategies hence compare labor market outcomes during months with droughts and months without shocks in a given city during a given year.

Because droughts are by construction exogenous, we do not need to control for individual characteristics (age, education, gender) to identify the impact of droughts on individual labor market outcomes. Our baseline model only includes shocks and not individual control covariates, consequently avoiding the “bad control” problem (Angrist and Pischke 2008). As a robustness check, we add individual controls to estimate a standard Mincer equation and shows that it does not change the results.

When we estimate the impact of droughts on the probability of an individual to be employed, we have preferred to use the linear probability model instead of a logit model. In a binary model, linear probability models are a convenient approximation of the response probability (Wooldridge 2010). A linear probability model also enables us to take into account spatial correlation between workers from the same city, contrary to MLE models.

When we estimate the impact of droughts on wage, hours worked and labor incomes, we provide sub-samples results for formal and informal workers. This sub-sample analysis is motivated by the hypothesis that informal workers are more exposed to shocks than formal ones due to social policies and labor laws in Latin America. LABLAC classifies workers as informal if they are self-employed, if they work for a private small firm (a firm with less than five employees). For similar reasons, we run the regressions on public sector workers who should be buffered from shocks as a robustness check.

5. EM-DAT is a global database on natural and technological disasters, containing essential core data on the occurrence and effects of more than 21,000 disasters in the world, from 1900 to present. EM-DAT is maintained by the Centre for Research on the Epidemiology of Disasters (CRED) at the School of Public Health of the Université catholique de Louvain located in Brussels, Belgium. In Latin America over the period covered by our study, large wet shocks are associated with floods events that happened for example in Colombia in 2005, in 2008, in 2009 and in 2011. Each time, those floods affected between 475,000 and 2.4 million people according to the EM-DAT dataset that tracks natural disasters. Despite disrupting daily life and potentially economic activity, each large wet spells has not resulted in important floods recorded by EM-DAT.

4 Empirical Results

4.1 Main results

Table 1 shows our estimates of the impact of small (top panel) and large (bottom panel) abnormal dry events on the probability of being employed, on the logarithm of hourly wages, on the logarithm of the number of hours worked per month, and on the logarithm of monthly labor incomes.

Column 1 presents the results of the impact of droughts on the probability of active individuals to be employed. They suggest that small dry deviations, whether they last for one or two months, do not impact the level of employment. However, large shocks that are sustained over two months have a significant negative impact on employment: the probability of active individuals to be employed is 1.2 percent lower when a city is experiencing a sustained large dry shock compared to a near normal weather period.

Columns 2 to 10 focus on labor market outcomes of employed workers. We find that shocks lasting for only one month have an extremely limited impact on labor market outcomes. Small shocks that last for one month affect the number of hours worked by formal workers only. This impact on hours worked is economically limited (+0.5 percent). As a consequence, with the wage hourly wage remaining constant, the increase in hours worked by formal workers does not translate into an increase of their monthly labor incomes. As for large shocks lasting for one month, we do not find statistical evidence that they affect labor market outcomes.

When abnormal level of rainfall are sustained over time (i.e., the definition of droughts), labor market outcomes of employed workers are impacted. It is particularly true for informal workers. Sustained small dry shocks decrease hourly wages of informal workers by 3.7 percent. This decrease is compensated by a similar increase in the number of hours worked (+3.2 percent), so that the monthly labor incomes of informal workers remain unchanged in the case of small sustained dry shocks.

Sustained large dry shocks have the most negative impact on occupied workers. They lead to a decrease of the number of hours worked (-5.5 percent) of informal workers. Cumulated to a (non significant) decrease in hourly wages (-2.6 percent), it translates into a significant decrease in labor monthly incomes is consequently consequent. We estimate that large sustained dry events cause a 8.1 percent decrease in monthly labor incomes of informal workers. Informal workers in LABLAC are both workers from small firms and workers from informal firms. Formal workers are however not impacted by large and sustained shocks. This absence of impact on their wages was expected as formal workers in Latin America are protected by social laws. One could have however expect an impact on the number of hours they work.

We report in appendix a number robustness checks. The standard equation in labor economics to explain wages is the Mincer equation, that includes the gender, the age, the square of age and education as control variables. Because dry shocks are by construction exogenous, we do not need to control for these variables. We show in Table A2 that adding these control variables in the regression does not change our results. In Table 1, find that informal workers are impacted but not formal workers. We believe that the strong social laws that protect formal workers in Latin America probably explain this results. With the same idea in mind, we believe that workers from the public sector should not be impacted by droughts, at the exception maybe of the number of hours worked. This is what we confirm in Table A3. The number of hours worked slightly increases with small dry shocks, and decreases with large dry shocks. These results are consistent with the ones displayed in Table 1. Yet and as expected, wages and incomes remain unchanged. In addition, as we focused on the rounds of surveys that are representative at the city level, we can collapse our database by city, construct a city-month panel on the average values of labor market incomes, and estimate it by specifying a full panel structure with city fixed effects. It is what we do in Appendix A4. Once again, we find

Table 1 – Droughts and Labor Market Outcomes

	All Active	All workers			Informal workers			Formal workers		
	Employment (1)	Wage (2)	Hours (3)	Labor Income (4)	Wage (5)	Hours (6)	Labor Income (7)	Wage (8)	Hours (9)	Labor Income (10)
Panel A: Small deviations										
Drought 1 month	0.001	-0.009	-0.001	-0.010	-0.002	-0.008	-0.010	-0.006	0.005**	-0.001
	(0.002)	(0.010)	(0.005)	(0.008)	(0.008)	(0.010)	(0.010)	(0.010)	(0.002)	(0.008)
Drought 2 months	-0.003	-0.032	0.016***	-0.016	-0.037***	0.032**	-0.004	-0.031	0.009**	-0.022
	(0.002)	(0.037)	(0.006)	(0.034)	(0.009)	(0.013)	(0.011)	(0.037)	(0.004)	(0.036)
Temperature	-0.000	0.003	0.000	0.004**	0.001	0.002***	0.003**	0.004*	-0.001	0.003**
	(0.000)	(0.002)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Lag 1 Temperature	-0.000	-0.008*	0.002	-0.007**	-0.005**	0.002	-0.004***	-0.009*	0.002	-0.007*
	(0.000)	(0.004)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.005)	(0.001)	(0.004)
R-squared	0.007	0.078	0.015	0.057	0.093	0.038	0.058	0.048	0.020	0.041
Panel B: Large deviations										
Drought 1 month	-0.001	0.008	-0.004	0.004	-0.005	0.000	-0.005	0.029	-0.007	0.021
	(0.002)	(0.016)	(0.009)	(0.021)	(0.010)	(0.014)	(0.020)	(0.021)	(0.007)	(0.021)
Drought 2 months	-0.012***	-0.030	-0.035*	-0.064*	-0.026	-0.055***	-0.081***	-0.008	-0.004	-0.012
	(0.003)	(0.025)	(0.020)	(0.038)	(0.016)	(0.019)	(0.027)	(0.026)	(0.018)	(0.028)
Temperature	0.000	0.003	0.000	0.004*	0.001	0.002***	0.003**	0.004*	-0.001	0.003**
	(0.000)	(0.002)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Lag 1 Temperature	-0.000	-0.008*	0.002	-0.007*	-0.005**	0.002	-0.004***	-0.009*	0.002	-0.007*
	(0.000)	(0.004)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.005)	(0.001)	(0.004)
R-squared	0.007	0.078	0.015	0.057	0.093	0.038	0.058	0.048	0.020	0.041
Observations	13,257,106	9,034,814	9,034,814	9,034,814	3,526,978	3,526,978	3,526,978	5,488,025	5,488,025	5,488,025

Notes: Standard errors in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Standard errors are clustered at the city level to account for spatial and temporal dependence. All specifications include city by year ($\eta_{j,y}$) and months by year (χ_m) fixed effects.

consistent results. The average probability of an active individual to be employed decreases with large repeated dry shocks. For employed workers, the number of hours worked decrease (-4 percent), leading to a decrease in labor incomes (-5.4 percent).

By construction, four consecutive months of small dry shocks bring a similar decrease in rainfall than two consecutive large shocks. As a robustness check, we also measure droughts by counting the number of deviations larger than one standard deviations up to four months instead of two as before. We display results in Table 2. We do not find that deviations up to four month impact the probability of employment. Consistently with Table 1, dry shocks that last over one month only do not impact the outcomes of workers. When dry shocks are repeated over two months, wages of informal workers decrease (-3.6 percent). This decrease is compensated by an increase in the number of hours worked (+5.4 percent). When shocks last for three months, informal workers' wages also decrease (-5.7 percent), and is this time not compensated by an increase in the number of hours worked. As a consequence, informal workers' labor incomes decreases by 5.8 percent. This result is also true when shocks last for four month. Interestingly for four months, formal workers also are impacted. Our results suggest that formal workers' wages decrease by 11.9 percent while their number of hours worked increase by 3.4 percent, leading to a decrease of labor incomes of 8.6 percent. This result differs from Table 1 where formal workers where not impacted by droughts.

4.2 Wet shocks and labor market outcomes

How labor markets respond to wet shocks? We replace droughts by their symmetric wet spells in Table 3. As oppose to droughts, our estimates suggest that wet shocks do not affect the level of employment, whether the shocks are small or large, short or sustained over time.

For employed workers, one month small wet spells decrease hourly wages and labor incomes of informal workers (-1.8 percent). As for large wet spells (the kind of deviation leading to floods), they affect both formal and informal workers. Large wet spells lasting over one month decrease the

Table 2 – Droughts and Labor Market Outcomes - Small variations sustained over four months

	All Active		All workers			Informal workers			Formal workers	
	Employment	Wage	Hours	Labor Income	Wage	Hours	Labor Income	Wage	Hours	Labor Income
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Sustained small deviations										
Drought 1 month	0.003	-0.012	-0.001	-0.012	-0.003	-0.003	-0.006	-0.008	0.003*	-0.005
	(0.002)	(0.009)	(0.004)	(0.008)	(0.008)	(0.008)	(0.009)	(0.007)	(0.002)	(0.006)
Drought 2 months	0.001	-0.018	0.020***	0.003	-0.036***	0.054***	0.018	-0.008	0.001	-0.007
	(0.002)	(0.037)	(0.007)	(0.035)	(0.005)	(0.014)	(0.016)	(0.039)	(0.005)	(0.038)
Drought 3 months	0.001	-0.028	0.003	-0.025	-0.057***	-0.000	-0.058**	-0.016	0.011***	-0.005
	(0.004)	(0.021)	(0.008)	(0.022)	(0.019)	(0.014)	(0.027)	(0.025)	(0.004)	(0.024)
Drought 4 months	-0.004	-0.085***	-0.006	-0.091***	-0.053**	-0.025	-0.078*	-0.119***	0.034*	-0.086**
	(0.009)	(0.030)	(0.020)	(0.032)	(0.021)	(0.022)	(0.041)	(0.043)	(0.018)	(0.035)
Temperature	0.000	-0.002	0.001	-0.001*	-0.002	0.001	-0.001	-0.002	0.001*	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.000)	(0.001)
Lag 1 Temperature	-0.001	0.001	0.002	0.004	-0.000	0.003	0.003	-0.002	0.001	-0.001
	(0.000)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)	(0.002)
Lag 2 Temperature	-0.000	-0.003**	-0.001	-0.004***	0.000	-0.000	0.000	0.001	-0.001	-0.001
	(0.000)	(0.001)	(0.001)	(0.001)	(0.003)	(0.001)	(0.002)	(0.002)	(0.001)	(0.001)
Lag 3 Temperature	0.001	-0.005	0.001	-0.004	-0.004	-0.002*	-0.006	-0.008*	0.002***	-0.005
	(0.000)	(0.003)	(0.001)	(0.003)	(0.003)	(0.001)	(0.004)	(0.004)	(0.001)	(0.003)
R-squared	0.007	0.083	0.016	0.060	0.098	0.041	0.057	0.048	0.019	0.043
Observations	9,622,357	7,675,744	7,675,744	7,675,744	2,971,277	2,971,277	2,971,277	4,685,584	4,685,584	4,685,584

Notes: Standard errors in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Standard errors are clustered at the city level to account for spatial and temporal dependence. All specifications include city by year ($\eta_{j,y}$) and months by year (χ_m) fixed effects.

hourly wage of formal workers by 4.6 percent. As the number of hours worked remain the same as without shocks, large wet shocks lasting over one month decrease formal workers' labor incomes by 3.9 percent. These coefficient are however significant only at a 10 percent level. Informal workers do not see a similar decrease in labor income with one month large wet shocks. Even if their number of hours worked decrease by 2.9 percent, informal workers see an increase in their hourly wage by 1.5 percent. The total effect on monthly labor incomes is therefore negative, but not significantly different from zero.

However, if large wet spells are sustained over time, informal workers see a 3 percent decrease in their hourly wages. These repeated large wet spells consequently decrease monthly labor incomes of informal workers by 1.8 percent - a result four times smaller than for droughts. In addition, this later coefficient is once again significant only at a 10 percent level. Hence, if wet spells do not impact the general level of employment as opposed to droughts, there is suggestive evidence that they impact the welfare of employed workers The total impact of wet spells on labor incomes is smaller than the impact of dry shocks.

Latin America is a data rich region. In Appendix 5, we provide additional robustness checks using alternative sources of data covering different cities, and different time periods. We show that our results are consistent if we use household surveys from the SEDLAC initiative, if we use entepirse surveys for 22 Latin American and Caribbean countries from the 2010 round that includes GPS coordinates. Results are also consistent when using administrative data on the universe of firms in Brazil between 2000 and 2013.

5 Pathways

Why do droughts negatively affect labor market outcomes in Latin American cities? We investigate two pathways that could drive the results: an increase in the number of power outages due to droughts, and a worsening of health conditions.

Table 3 – Wet Spells and Labor Market Outcomes

	All Active	All workers			Informal workers			Formal workers		
	Employment	Wage	Hours	Labor Income	Wage	Hours	Labor Income	Wage	Hours	Labor Income
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Panel A: Small deviations										
Wet spell 1 month	-0.000	-0.012***	0.003	-0.009**	-0.018***	0.001	-0.018***	0.000	0.005	0.005
	(0.001)	(0.004)	(0.002)	(0.004)	(0.005)	(0.002)	(0.006)	(0.005)	(0.003)	(0.005)
Wet spell 2 months	0.001	0.002	0.012**	0.014	-0.017	0.020	0.003	0.014	0.006	0.020
	(0.003)	(0.008)	(0.006)	(0.010)	(0.012)	(0.015)	(0.008)	(0.016)	(0.004)	(0.016)
Temperature	0.000	0.003	0.000	0.004*	0.001	0.002**	0.003**	0.004*	-0.001	0.003**
	(0.000)	(0.002)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Lag 1 Temperature	-0.000	-0.008*	0.002	-0.007*	-0.005**	0.002	-0.004***	-0.009*	0.002	-0.007*
	(0.000)	(0.004)	(0.001)	(0.003)	(0.002)	(0.002)	(0.001)	(0.005)	(0.001)	(0.004)
R-squared	0.007	0.078	0.015	0.057	0.093	0.038	0.058	0.048	0.020	0.041
Panel B: Large deviations										
Wet spell 1 month	0.001	-0.021	-0.006	-0.027*	0.015***	-0.029**	-0.014	-0.046*	0.006	-0.039*
	(0.001)	(0.015)	(0.004)	(0.016)	(0.005)	(0.013)	(0.011)	(0.023)	(0.004)	(0.020)
Wet spell 2 months	0.001	-0.012	0.004	-0.008	-0.030**	0.011	-0.018*	0.003	-0.007	-0.003
	(0.002)	(0.011)	(0.005)	(0.014)	(0.012)	(0.016)	(0.010)	(0.018)	(0.004)	(0.016)
Temperature	0.000	0.003	0.000	0.004**	0.001	0.002***	0.003**	0.004*	-0.001	0.003**
	(0.000)	(0.002)	(0.000)	(0.002)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Lag 1 Temperature	-0.000	-0.008*	0.002	-0.007*	-0.005**	0.002	-0.004***	-0.009*	0.002	-0.007*
	(0.000)	(0.004)	(0.001)	(0.003)	(0.002)	(0.001)	(0.001)	(0.005)	(0.001)	(0.004)
R-squared	0.007	0.078	0.015	0.057	0.093	0.038	0.058	0.048	0.020	0.042
Observations	13,257,106	9,034,814	9,034,814	9,034,814	3,526,978	3,526,978	3,526,978	5,488,025	5,488,025	5,488,025

Notes: Standard errors in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Standard errors are clustered at the city level to account for spatial and temporal dependence. All specifications include city by year ($\eta_{j,y}$) and months by year (χ_m) fixed effects.

5.1 Droughts and power outages

Generating electricity is highly water intensive (Fthenakis and Kim 2010) and several examples over the last years have highlighted the threat water scarcity can represent for electricity provision in the region. [6] When excessive rainfall are followed by floods or landslides, large wet shocks might also cause an increase in power outages because of the damages on infrastructures. We use enterprise surveys to explore the link between droughts and the occurrence of water outages for firms.

Enterprise Surveys are harmonized firms surveys conducted by the World Bank. They contains data for formal private manufacturing firms with five or more employees. The firm level data is representative at the national level based on random stratified sampling with sector, size, and location being the strata. The survey targets business owners and top managers of firms as respondents. We compile for this analysis Enterprise Surveys from all available LAC countries for which GPS coordinates are available. The sample covers 22 LAC countries and has data for 2010. The Enterprise Surveys data has several advantages including being comparable across countries. The surveys cover a wide range of topics on the business environment that typical census firm level data does not include. Of primary interest for us, the enterprise surveys provide information on the occurrence of electricity outages experienced by firms. We use this information to test if rainfall shocks cause an increase in power outages. We test the model:

$$PowerOut_{i,j,k} = \alpha + \beta_1 1SD_j^+ + \beta_2 2SD_j^+ + \beta_3 1SD_j^- + \beta_4 2SD_j^- + \tau_1 Temperature_j + \gamma_1 Country_k + \epsilon_{i,j} \quad (2)$$

6. For instance, Brazil's power sector is dominated by hydropower, which accounts for two-thirds of the total installed capacity. Heavy dependence on hydropower makes Brazil vulnerable to power-supply shortages in the case of long periods of drought. This dependence is expected to decrease in the future thanks to the deployment of wind and solar projects that have been contracted in recent years (World Bank 2016).

Where $PowerOut_{i,j}$ is the typical number of power outages experienced by firm i in region j from country k during a month of the year 2010. Enterprise surveys being annual, we construct our shocks variables by counting the number of months with weather deviations during the year and we treat the variables as continuous variables. Results are displayed in Table 4. We consistently find that large shocks increase the number of power outages in Latin America. An additional month with large dry shock during the year increase the number of power outages by 0.7, which correspond to a 33 percent increase. This impact of large dry shocks is two times larger than the impact of large wet shocks (+0.2 to +0.29). When controlling for firms' characteristics for robustness, results also suggest that small abnormal deviations increase the number of power outages. The increase in outages is however ten times lower with small shocks than with large shocks, accrediting that it is not passed on to labor market outcomes.

Table 4 – Droughts and power outages in Latin America

	Shocks	Shocks + controls
Total No of Negative 1 SD Prec shocks	0,003	0,006**
	(0,003)	(0,003)
Total No of Negative 2 SD Prec shocks	0,070***	0,075***
	(0,023)	(0,014)
Total No of Positive 1 SD Prec shocks	0,002	0,004
	(0,003)	(0,004)
Total No of Positive 2 SD Prec shocks	0,029***	0,030***
	(0,007)	(0,006)
Average Monthly Temp for the Year	0,0001	-0,0002
	(0,000)	(0,001)
Number of observations	7 610	4 303

Notes: Standard errors in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. All specifications include country, and sector 2-digits fixed effects. In column 2, firms' level controls are: Firms own a generator (Y/N), Bribery depth (% of public transactions where a gift or informal payment was requested), Bribery incidence (Firms experiencing at least one bribe payment request Y/N), Firm size (Log of total number of employees), % of firms buying fixed assets, Establishment has checking or savings account at this time, Establishment has a line of credit or loan at this time, Losses due to breakage/spoilage shipped domestically (% of value of the products), Security costs (% of sales), Log of age of firm, Gender of the manager, Nationality of ownership (foreign or not), Exports 10% or more of sales, Number of years firm was unregistered at start, Use technology licensed from foreign companies and a constant term.

5.2 Health

While Latin America enjoys relatively high water access (especially in urban areas), the quality and safety of water and sanitation infrastructure remain insufficient – particularly in terms of sanitation. Indeed, sewerage access is low and less than 30 percent of wastewater is being treated, an inadequate level given the level of income and urbanization of the region. The health consequences of those access gaps are tangible. As of 2015, a loss of over 2 million disability-adjusted life years (DALYs) were attributable to unsafe water and sanitation (WASH), with over a quarter of those attributable to Brazil alone (Institute for Health Metrics 2015).[7]

Incidentally, health ranks high in terms of the potential pathways through which droughts may affect households and workers through a deterioration of the quality of their environment leading to

7. DALY stands for disability-adjusted life year. It is a metric that allows researchers and policymakers to compare different populations and health conditions across time. DALYs equal the sum of years of life lost (YLLs) and years lived with disability (YLDs). One DALY equals one lost year of healthy life. DALYs allow us to estimate the total number of years lost due to specific causes and risk factors at the country, regional, and global levels. The sum of DALYs lost across a given population can be thought of as a measure of the gap between current health status and an ideal health situation where the entire population lives to an advanced age, free of disease and disability. (Source. IHME)

a higher risk of contamination and a higher occurrence of epidemic diseases. This pathway could be a direct one, impacting the health of the income earner, or an indirect one resulting from the need to care for another sick person (child, family member etc.).

We construct a dataset on health outcomes using hospital micro data from Brazil (Datasus) between 2000 and 2013 to study this pathway. The dataset records hospital admissions every month over the period, representing about 39.5 million patients and provides information on, among other, the reasons of the admission of the patient. We collapse the data to construct a monthly panel at the municipality level (the lowest administrative division in Brazil). The administrative division used for the panel is the municipality where the hospital is located, and not the municipality where the patient lives. As our focus is on urban areas and most urban areas have at least one hospital within their boundaries limits, it is unlikely that the households would go to a hospital located in a different municipality than the one where they reside. [8] It is also unlikely that they go in a hospital located in a city far from the one where they live. Hence, the municipality of the hospital is experiencing the same weather than the municipality of residence of the patient.

We merge Datasus with official population counts provided annually by the Brazilian Institute of Geography and Statistics (IBGE), and with the Brazilian weather dataset by Xavier, King, and Scanlon (2015). This weather dataset is available at a finer scale than Willmott, Matsuura, and Legates (2001) (0.25 x 0.25 degree) and is arguably, more precise thanks to the use of 3,625 rain gauge and 735 weather stations. Our focus for this paper being urban areas, we classify a municipality as an urban one if its urban population is larger than its rural population.

To estimate the impact of shocks on health outcomes, we use municipality and month by year fixed effects to control for unobserved fixed characteristics and time variations. The model estimated is:

$$ln(HealthOutcome)_{i,t} = \beta Drought^{k}_{i,t} + \tau_1 Temperature_i + \gamma_i + \mu_t + \epsilon_{i,t} \tag{3}$$

On the left hand side, we focus on the logarithm of hospital admissions. We limit the analysis to admissions not related to alcohol consumption, diabetes or for psychiatric reasons. Following the medical literature, we also focus on diarrhea cases for which we have information for children under 2 years old and that is expected to be influenced by rainfall through an increased environmental contamination. As those cases are registered at the hospital level, they are likely to be more severe, having required parents to bring their child to the hospital. There are good reasons to believe that a spike in diarrhea cases at hospital level is likely echoed by a corresponding if not larger incidence of diarrhea in children not requiring hospitalization but likely disruptive for their parents' time allocation and thus a good proxy for this health pathway. Variables on the right hand side are similar to equation (1), already defined this time with the Brazilian weather data.

Our results support this pathway (Table 5). They confirm that shocks, and particularly droughts, increase the number of hospital admissions in Brazil. The effect of small dry shocks and large dry shocks on both hospital admission and the number of case of diarrhea are significant, even if mostly urban areas. The effect of contemporary small shocks is at least five times lower than the impact of large dry deviations. Small dry shocks lead to 0.6 percent increase in hospital admissions in both rural and mostly urban municipalities, and to a 1.2 percent increase in the cases of diarrhea. This impact on diarrhea cases is however not significant when limiting the analysis to mostly urban municipalities. Large dry shocks increase the number of hospital admissions in Brazilian municipalities by 3.8 percent as compared to a near normal weather month, and even by 4.8 percent when focusing on mostly

8. With the possible exception of households living close to the border of another municipality. However, as a number of social programs have a municipal focus, households are likely to indeed attend facilities located in their municipality of residence.

urban municipalities. They also increase the number of cases of diarrhea by 5.2 percent compared to near normal weather year in an average Brazilian municipality, and by 5.9 percent in a mostly urban municipality. Interestingly, when looking at the impact of similar wet shocks, we find a smaller impact. Small or large wet shocks lead to 1.2 increase in the number of diarrhea. The increase if of 2.2 percent when shocks are large in mostly urban municipalities. We however do not see an impact of wet shocks on the level of admissions.

Table 5 – Droughts and Health Outcomes

	All Municipalities		Predominantly Urban Municipalities	
	Admissions	Diarrhea	Admissions	Diarrhea
	(1)	(2)	(3)	(4)
Panel A				
Small dry shock	0.006***	0.012***	0.006*	0.004
	(0.002)	(0.003)	(0.003)	(0.004)
Temperature	-0.012***	-0.013***	-0.014***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
Panel B				
Large Dry shock	0.038*	0.052*	0.048*	0.059*
	(0.022)	(0.028)	(0.027)	(0.034)
Temperature	-0.011***	-0.013***	-0.014***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
Panel C				
Small wet shock	0.002	0.013***	0.005	0.012***
	(0.002)	(0.003)	(0.003)	(0.004)
Temperature	-0.011***	-0.013***	-0.014***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
Panel D				
Large wet shock	-0.003	0.012***	-0.001	0.022***
	(0.003)	(0.005)	(0.004)	(0.006)
Temperature	-0.011***	-0.013***	-0.014***	-0.006***
	(0.001)	(0.001)	(0.001)	(0.002)
Observations	852,857	754,037	549,289	475,372
Number of Municipalities	5,490	5,484	3,544	3,541

Notes: Standard errors in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. All specifications include municipality and month by year fixed effects. Municipalities are classified as mostly urban when the urban population in the municipality is larger than the rural population, based on IBGE data.

6 Discussion and Conclusion

In this paper, we have highlighted that cities' economies are sensitive to droughts in Latin America, and that, maybe surprisingly and so far undocumented, the impact of droughts on labor market outcomes is larger than the impact of wet shocks, including the ones causing floods. When a drought hits a city, the probability of being employed for active inhabitants decreases, the labor incomes in the informal sector decreases. Our pathways analyzes suggest that a decrease in productivity can explain our results, whether it is because of power outages or health deterioration of workers.

If the evidence of an impact of droughts for formal workers is less systematic than for informal workers, formal sectors firms also are impacted by droughts, as confirmed in appendix. In Latin America, social laws are particularly protective for (formal) workers. It is then unlikely that firms decrease their workers' wages. On the contrary, they adapt by adjusting their sizes. Informal workers are more likely to be poorer than the rest of the population (Table A6). They also are most likely affected by shocks. Hence, shocks seem to impact poor or vulnerable households more frequently than richer households in the context of Latin American metropolitan areas. In a context, of economic slowdown for the region, the vulnerability of labor incomes of poor households - a key tenant of poverty reduction - to shocks is especially preoccupying.

The strong impact of droughts constitutes a novel result departing from existing literature, including the different IPCC reports that have strongly emphasized the risk of floods for cities. Finding these results in a region much better endowed than most of the developing world – compared for instance to South Asia or Sub-Saharan Africa - is of particular interest. This emphasizes the need to better account for those risks in the planning of infrastructure investments, including in the extension of the analysis of their cost-effectiveness to include considerations related to different scenarios of climatic vulnerability.

Looking forward, the analysis raises three areas needing further research. First, health and power outages might not be the only pathways explaining this impact of droughts. If agriculture is the thirstiest economic sector, other sectors rely on water for their production activities. Such sector can include manufacturing, construction or mining firms. It might be the case that because of water outages, these firms are directly impacted by droughts. This question is hard to investigate with our data. The surveys we use are representative at a city level. They are not meant to be representative for each sectors. Additional research based on administrative data on firms instead of survey data would be able to study firms' dynamics by sector and see if sectors that are relatively more water intensive are more affected by droughts.[9] The results of our analysis have cross-sectoral policy implications. First, in the larger context of climate change, our analysis shows a multi-faceted vulnerability of cities to large shocks (mainly dry but also wet) that cities infrastructure appears insufficient to buffer, even in one of the world best endowed middle income regions in terms of infrastructure.

Second, our results confirm the need to understand better the role of water and sanitation infrastructure in weathering climate variability and water stress in low and middle-income countries. This issue of urban water infrastructure has been raised in the water resource management literature (McKinsey 2009). At the exception of Ashraf et al. (2017), the economic literature notably lags in terms of research that could shed light on the type of infrastructure and the level of coverage required not only to respond to the demand of cities but also to absorb water variability.

Third, beyond metropolitan areas and "primate cities" (Jefferson 1939) a need exists to also look at the exposure and impact of secondary cities and small towns, that are less well endowed with infrastructure and where poverty tends to be higher (Ferré, Ferreira, and Lanjouw 2012). As noted by Christiaensen and Kanbur (2017) , not only do two-fifths of the urban population live in small towns of less than 250,000 but urban centers of less than 1 million will absorb the majority of the population growth in coming years (Laros and Jones 2014). Fay et al. (2017) also flags this issue as important for the region in light of the evolution of its urbanization patterns. With dwindling density already observed in some of the large metropoles of our analysis (Buenos Aires, Brasilia, Santiago, or Montevideo among others) as a result of transport, land use and housing policies, the implications for infrastructure investments and maintenance costs in a context of higher climate variability are ever more pressing and foreboding for other regions.

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Appendix

Table A1 – Rounds of survey LABLAC and Enterprise Surveys

Countries	LABLAC Monthly Data Nb. Cities	LABLAC Monthly Data Years	Enterprise Surveys Annual Data Year
Argentina	-	-	2010
Belize	-	-	2010
Bolivia	-	-	2010
Brazil	6	2005-2014	2010
Chile	9	2010-2014	2010
Columbia	22	2008-2014	2010
Cost Rica	-	-	2010
Ecuador	5	2006-2014	2010
El Salvador	1	2010-2013	2010
Guatemala	-	-	2010
Guyana	-	-	2010
Honduras	-	-	2010
Jamaica	-	-	2010
Mexico	32	2005-2014	2010
Nicaragua	-	-	2010
Panama	-	-	2010
Paraguay	1	2005-2014	2010
Peru	1	2005-2014	2010
Paraguay	-	-	2010
St. Vincent and Grenadines	-	-	2010
Surniname	-	-	2010
Trinidad and Tobago	-	-	2010
Uruguay	1	2006-2014	2010
Venezuela	-	-	2010
Total cities - firms	78		
Observations	12,230,393		
Population of	308,885,074		

Table A2 – Droughts and Labor Market Outcomes - Mincer Equation

	All Active	All workers			Informal workers			Formal workers		
	Employment	Wage	Hours	Labor Income	Wage	Hours	Labor Income	Wage	Hours	Labor Income
Panel A: Small deviations										
Drought 1 month	0.002	-0.000	0.001	0.000	0.004	-0.004	0.000	-0.004	0.005**	0.001
	(0.002)	(0.003)	(0.004)	(0.004)	(0.006)	(0.010)	(0.009)	(0.002)	(0.002)	(0.003)
Drought 2 months	-0.003	-0.017**	0.018***	0.001	-0.031***	0.035***	0.004	-0.007	0.008	0.002
	(0.002)	(0.008)	(0.005)	(0.008)	(0.007)	(0.013)	(0.011)	(0.010)	(0.005)	(0.013)
Temperature	-0.000	0.001	0.000	0.001	-0.000	0.002**	0.001*	0.001	-0.001	0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag 1 Temperature	-0.000	-0.004**	0.002	-0.002***	-0.004***	0.001	-0.003***	-0.003*	0.001	-0.002*
	(0.000)	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Gender	0.021***	0.208***	0.189***	0.397***	0.168***	0.258***	0.426***	0.168***	0.111***	0.279***
	(0.005)	(0.016)	(0.019)	(0.034)	(0.027)	(0.031)	(0.055)	(0.018)	(0.014)	(0.029)
Age	0.011***	0.040***	0.028***	0.068***	0.034***	0.031***	0.065***	0.036***	0.024***	0.060***
	(0.001)	(0.003)	(0.004)	(0.005)	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)	(0.005)
Age square	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary incomplete	-0.002	0.167***	0.012	0.179***	0.106***	0.003	0.108***	0.154***	0.011**	0.165***
	(0.006)	(0.018)	(0.015)	(0.027)	(0.015)	(0.014)	(0.024)	(0.027)	(0.006)	(0.024)
Primary complete	-0.009	0.321***	0.044**	0.364***	0.220***	0.044**	0.264***	0.276***	0.019***	0.295***
	(0.005)	(0.013)	(0.019)	(0.028)	(0.011)	(0.018)	(0.023)	(0.027)	(0.007)	(0.024)
Secondary incomplete	-0.013***	0.446***	0.034**	0.480***	0.284***	0.023	0.307***	0.425***	0.005	0.430***
	(0.005)	(0.027)	(0.014)	(0.033)	(0.026)	(0.017)	(0.032)	(0.020)	(0.014)	(0.023)
Seconddary complete	-0.013**	0.659***	0.072***	0.731***	0.432***	0.044***	0.476***	0.604***	0.002	0.605***
	(0.006)	(0.030)	(0.009)	(0.032)	(0.034)	(0.012)	(0.041)	(0.024)	(0.016)	(0.030)
College incomplete	-0.019***	0.977***	-0.000	0.977***	0.708***	-0.092***	0.615***	0.892***	-0.078***	0.814***
	(0.007)	(0.034)	(0.018)	(0.044)	(0.054)	(0.028)	(0.073)	(0.026)	(0.015)	(0.023)
College complete	0.003	1.487***	0.023	1.510***	0.882***	0.077***	0.960***	1.306***	-0.109***	1.197***
	(0.008)	(0.047)	(0.019)	(0.054)	(0.106)	(0.016)	(0.107)	(0.045)	(0.014)	(0.047)
R-squared	0.039	0.364	0.074	0.354	0.172	0.097	0.193	0.362	0.088	0.336
Panel B: Large deviations										
Drought 1 month	-0.000	0.001	-0.004	-0.003	-0.007	0.003	-0.005	0.012	-0.005	0.007
	(0.002)	(0.008)	(0.009)	(0.013)	(0.009)	(0.013)	(0.018)	(0.013)	(0.007)	(0.015)
Drought 2 months	-0.012***	-0.004	-0.035	-0.039	-0.015	-0.060**	-0.076**	0.024*	-0.002	0.022
	(0.003)	(0.009)	(0.025)	(0.030)	(0.012)	(0.026)	(0.030)	(0.014)	(0.017)	(0.018)
Temperature	-0.000	0.001	0.000	0.001	-0.000	0.002**	0.001*	0.001	-0.001	0.000
	(0.000)	(0.001)	(0.000)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Lag 1 Temperature	-0.000	-0.004**	0.002	-0.002***	-0.004***	0.001	-0.003***	-0.003*	0.001	-0.002*
	(0.000)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)	(0.002)	(0.001)	(0.001)
Gender	0.021***	0.208***	0.189***	0.397***	0.168***	0.257***	0.426***	0.168***	0.111***	0.279***
	(0.005)	(0.016)	(0.019)	(0.034)	(0.027)	(0.031)	(0.055)	(0.018)	(0.014)	(0.029)
Age	0.011***	0.040***	0.028***	0.068***	0.034***	0.031***	0.065***	0.036***	0.024***	0.060***
	(0.001)	(0.003)	(0.004)	(0.005)	(0.002)	(0.004)	(0.004)	(0.003)	(0.002)	(0.005)
Age square	-0.000***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***	-0.000***	-0.000***	-0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Primary incomplete	-0.002	0.167***	0.012	0.179***	0.106***	0.002	0.108***	0.154***	0.011**	0.165***
	(0.006)	(0.018)	(0.015)	(0.027)	(0.015)	(0.014)	(0.024)	(0.027)	(0.006)	(0.024)
Primary complete	-0.009	0.321***	0.044**	0.364***	0.220***	0.044**	0.264***	0.276***	0.019***	0.295***
	(0.005)	(0.013)	(0.019)	(0.028)	(0.011)	(0.018)	(0.023)	(0.027)	(0.007)	(0.024)
Secondary incomplete	-0.013***	0.446***	0.034**	0.480***	0.284***	0.023	0.307***	0.426***	0.005	0.430***
	(0.005)	(0.027)	(0.014)	(0.033)	(0.027)	(0.017)	(0.032)	(0.020)	(0.014)	(0.023)
Seconddary complete	-0.013**	0.659***	0.072***	0.731***	0.432***	0.044***	0.476***	0.604***	0.002	0.605***
	(0.006)	(0.030)	(0.009)	(0.032)	(0.034)	(0.012)	(0.041)	(0.024)	(0.016)	(0.030)
College incomplete	-0.019***	0.977***	-0.000	0.977***	0.708***	-0.093***	0.615***	0.892***	-0.078***	0.814***
	(0.007)	(0.034)	(0.018)	(0.044)	(0.054)	(0.028)	(0.073)	(0.026)	(0.015)	(0.023)
College complete	0.003	1.487***	0.023	1.510***	0.882***	0.077***	0.960***	1.306***	-0.109***	1.197***
	(0.008)	(0.047)	(0.019)	(0.054)	(0.106)	(0.016)	(0.107)	(0.045)	(0.014)	(0.047)
R-squared	0.039	0.364	0.074	0.354	0.172	0.097	0.193	0.362	0.088	0.336
Observations	13,205,379	8,992,782	8,992,782	8,992,782	3,507,779	3,507,779	3,507,779	5,465,291	5,465,291	5,465,291

Notes: Standard errors in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Standard errors are clustered at the city level to account for spatial and temporal dependence. All specifications include city by year ($\eta_{j,y}$) and months by year (χ_m) fixed effects.

Table A3 – Droughts and Labor Market Outcomes - Public Sector Workers

	Public sector workers		
	Wage	Hours	Labor Income
	(1)	(2)	(3)
Panel A: Small deviations			
Drought 1 month	-0.009	0.005	-0.005
	(0.012)	(0.003)	(0.013)
Drought 2 months	-0.014	0.024**	0.010
	(0.021)	(0.011)	(0.028)
Temperature	0.000	-0.004	-0.003
	(0.002)	(0.003)	(0.003)
Lag 1 Temperature	0.000	0.003	0.004
	(0.002)	(0.002)	(0.003)
R-squared	0.081	0.051	0.063
Panel B: Large deviations			
Drought 1 month	0.017	-0.028**	-0.011
	(0.024)	(0.013)	(0.020)
Drought 2 months	0.053	-0.004	0.049
	(0.070)	(0.017)	(0.058)
Temperature	0.000	-0.004	-0.003
	(0.002)	(0.003)	(0.003)
Lag 1 Temperature	0.000	0.003	0.004
	(0.003)	(0.002)	(0.003)
R-squared	0.081	0.051	0.063
Observations	977,997	977,997	977,997

Notes: Standard errors in parentheses. *, **, and *** indicate significance at the 10, 5, and 1% level, respectively. Standard errors are clustered at the city level to account for spatial and temporal dependence. All specifications include city by year ($\eta_{j,y}$) and months by year (χ_m) fixed effects.

Table A4 – Droughts and Labor Market Outcomes - City panel

	All Active	All workers		
	Employment	Wage	Hours	Labor Income
	(1)	(2)	(3)	(4)
Panel A: Small deviations				
Drought 1 month	-0.001	-0.008	-0.003	-0.011
	(0.001)	(0.010)	(0.003)	(0.010)
Drought 2 months	0.000	-0.009	0.000	-0.009
	(0.002)	(0.017)	(0.005)	(0.017)
Temperature	-0.000*	0.009***	0.001	0.010***
	(0.000)	(0.003)	(0.001)	(0.002)
Lag 1 Temperature	-0.000**	-0.006***	-0.001	-0.007***
	(0.000)	(0.002)	(0.001)	(0.002)
R-squared	0.508	0.438	0.309	0.419
Panel B: Large deviations				
Large deviations				
Drought 1 month	-0.000	-0.021	0.005	-0.016
	(0.002)	(0.017)	(0.006)	(0.020)
Drought 2 months	-0.005***	-0.014	-0.040*	-0.054**
	(0.001)	(0.010)	(0.022)	(0.021)
Temperature	-0.000*	0.009***	0.000	0.010***
	(0.000)	(0.003)	(0.001)	(0.002)
Lag 1 Temperature	-0.000**	-0.006***	-0.001	-0.007***
	(0.000)	(0.002)	(0.001)	(0.002)
R-squared	0.507	0.438	0.309	0.419
Observations	7,513	4,362	4,362	4,362
Number of groups	78	78	78	78

A5: Additional robustness checks using alternative datasets

Household surveys

We use for our main results multiple rounds of labor force surveys compiled by the CEDLAS project. The CEDLAS project has also harmonized household surveys through the Socio-Economic Database for Latin America and the Caribbean (SEDLAC) initiative. As opposed to labor force surveys that are monthly, households surveys in SEDLAC are annual. Identification of a direct impact of droughts on labor market outcomes is therefore less precise. Labor market outcomes in SEDLAC are recall question on wages, earnings and hours worked during a typical month of the past calendar year. Data hence mix information on labor outcomes during the shock and during the recovery period. As a third robustness check, we compile all the rounds of SEDLAC surveys that are representative at the metropolitan area level to confirm LABLAC results. The dataset covers around 2,000,000 active occupied individuals living in 56 metropolitan areas in three countries (Argentina, 1998-2012; Brazil, 1992-2012, and Colombia, 2008-2014).

We construct shocks variables as the number of months with shocks during a year, and treat them as continuous variables. As in equation (1), we control for annual temperature, and we add year and cities fixed effects. Results are displayed in Table A5.1. As with LABLAC, small negative shocks are found to have no impact of labor outcomes. Large dry shocks them have an impact. An additional large dry shock decreases labor incomes by 4.6 percent. As for wet shocks, small wet shocks are associated with a small increase in labor incomes (+0.7 percent). Large wet shock decreases labor incomes by a bit more than one percent. Hence consistently with LABLAC, the negative impact of large dry shocks is four times larger than the impact of large wet shocks.

Contrary to LABLAC, non-labor incomes are consistently reported in SEDLAC, allowing us to look at the impact of shocks on them. Because a high proportion of non-labor incomes are public transfers (social transfers, pensions etc.) [10], we expect them to be less sensitive to shocks. Table A5.1 shows that small dry shocks do not decrease non-labor incomes. As for large dry shocks, they once again do decrease non-labor incomes. for all small shocks and for large wet shocks, non-labor incomes do not vary following shocks. Non-labor incomes do not decrease because of the shocks but neither do they increase to buffer the negative impact of large wet shocks on labor incomes. Thus, the combined total incomes decrease with large wet shocks (i.e., negatively affected labor income and stable non-labor incomes). In the case of large dry shocks, the situation is worse. For informal workers, non-labor incomes significantly decrease after large dry shocks. Our analysis suggests that the impact on non-labor incomes is up to two times larger than the impact on labor incomes. Their total incomes are then affected by both a decrease in labor and non-labor incomes.

10. Pensions and transfers account for two-third of total non-labor incomes in our LABLAC database.

	Labor Income						Non-Labor Income					
	(1) Active Pop	(2) Informal	(3) Formal	(4) Self Employed	(5) Large Firms	(6) Small Firms	(7) Active Pop	(8) Informal	(9) Formal	(10) Self Employed	(11) Large Firms	(12) Small Firms
Small Positive Shocks	0.007*	0.009**	0.005	0.010**	0.007**	0.009**	-0.007	-0.007	0.001	-0.002	0.005	-0.007
	(0.004)	(0.004)	(0.003)	(0.004)	(0.004)	(0.004)	(0.012)	(0.008)	(0.018)	(0.010)	(0.017)	(0.010)
Small Negative Shocks	0.001	0.002	0.004	0.002	0.005	0.004	0.009	-0.006	0.020	-0.007	0.021	-0.007
	(0.004)	(0.005)	(0.003)	(0.006)	(0.003)	(0.005)	(0.013)	(0.011)	(0.019)	(0.012)	(0.018)	(0.012)
Large Positive Shocks	-0.013**	-0.012*	-0.013**	-0.015*	-0.016***	-0.012*	-0.005	0.002	-0.010	0.005	0.000	-0.001
	(0.006)	(0.007)	(0.005)	(0.008)	(0.006)	(0.007)	(0.010)	(0.008)	(0.018)	(0.009)	(0.017)	(0.010)
Large Negative Shocks	-0.046*	-0.060*	-0.065**	-0.053	-0.061**	-0.067**	-0.071	-0.138***	-0.053	-0.103**	-0.116	-0.124**
	(0.028)	(0.033)	(0.029)	(0.039)	(0.024)	(0.033)	(0.054)	(0.044)	(0.070)	(0.044)	(0.072)	(0.053)
Average Temperature	0.077	-0.087	0.097**	-0.142**	0.084*	-0.066	-0.277**	-0.226**	-0.662***	-0.193*	-0.677***	-0.216**
	(0.063)	(0.065)	(0.047)	(0.067)	(0.050)	(0.070)	(0.119)	(0.107)	(0.200)	(0.099)	(0.219)	(0.109)
Average Temperature sq	-0.002	0.001	-0.002**	0.002	-0.002*	0.001	0.006**	0.006**	0.015***	0.005**	0.016***	0.005**
	(0.001)	(0.001)	(0.001)	(0.002)	(0.001)	(0.002)	(0.003)	(0.003)	(0.005)	(0.002)	(0.005)	(0.003)
Constant	4.743***	6.501***	4.897***	7.402***	4.801***	6.244***	6.792***	6.093***	11.072***	5.975***	9.950***	6.353***
	(0.691)	(0.729)	(0.524)	(0.756)	(0.544)	(0.774)	(1.349)	(1.171)	(2.310)	(1.171)	(2.429)	(1.273)
Observations	2,086,298	780,249	1,078,798	413,161	710,774	869,033	319,095	129,712	113,469	70,749	63,712	147,213
R-squared	0.104	0.115	0.077	0.135	0.105	0.111	0.082	0.119	0.077	0.139	0.096	0.115
Individual controls	No	No	No	No	No	No	No	No	No	No	No	No
City FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES
Year FE	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES	YES

Table A5.1 – SEDLAC

Firms data

Results in Table 1 suggest that droughts have an impact on employment levels in urban areas, but that wet spells have no impact on employment. We also find that formal workers' wages are greatly unaffected by droughts in LABLAC, confirming that if firms are impacted, they had to decrease their margins or slow down their growth. We confirm this by looking at the impact of droughts using firms data from harmonized surveys of the LAC region, and from administrative sources in Brazil.

Using enterprise surveys, we specify our model as follows:

$$EmpGrowth_{i,k,j,r} = \alpha + \beta_1 1SD_j^- + \beta_2 2SD_j^- + \beta_3 1SD_j^- + \beta_4 2SD_j^- \\ + \tau_1 Temperature_j + \lambda ln(Size)_{i,j,r} + \gamma_{1,k} + \gamma_{2,r} + \epsilon_{i,j,k,r} \quad (4)$$

Where $Empgrwth$ is the annual growth in employment for firm i located in region j from country k and sector (within manufacturing) r between the fiscal year referenced in the survey (l1) and the two fiscal years preceding it (l2). The growth rate is calculated as $(l1-l2)/[l1+l2[/2$. Our main precipitation shock variables are the number of months a firm has experienced precipitation one and two standard deviations below and above the long run average precipitation during l2. Precipitation shocks are taken for the beginning of the period of the employment growth, as it is more likely to be a predictor of growth of total employment. We also control for temperature during l2. As in a standard growth equation, we account for the size of the firm in terms of total employment two fiscal years ago ($lnSize$). This is because employment two fiscal years ago is more likely to be a predictor of employment growth, than total employment in the last fiscal year. Finally, we include country and two-digit level ISIC sector (within manufacturing) fixed effects. Our identification strategies for shocks relies here on the differences in rainfall between firms from the same sector inside a given country.

Enterprise surveys provides information on the quality of water infrastructures firms enjoy. In an extended specification, we control for these infrastructures and study the correlation between the occurrence of water outages and employment growth. In this setting, we control for several firm characteristics to avoid an omitted variable bias. They include the age of the firm, foreign ownership, exporter status, security cots, generator ownership, and relationship to the informal sector in terms of competition, and whether the firm was informal before becoming formal.

Results are presented in Table A5.2. They suggest that in the case of a small wet shocks, the rate of employment growth within firms slightly increases. The impact remains however economically limited. In the case of small dry shocks or large wet shocks, firms' hiring decisions do not seem to be impacted however. In contrast, and consistent with our previous results, when large dry shocks occur, firms slow down the hiring of new workers over the following year: firms' size growth rate is 14 percent to 23 percent slower during a year with a large dry shock compared to a normal year. The enterprise surveys also provide information on the number and length of water outages experienced by firms during the year of the survey. In line with previous results, the more frequent the water outages, the slower the growth of employment rate.

Table A5.2 – Enterprise Surveys: Precipitation and Employment growth

	Employment Growth	
	(1)	(2)
	Parsimonious	**Firms controls + infrastructures**
Total No of Positive 1 SD Prec shocks	2.970*	2.888**
	(1.694)	(1.389)
Total No of Positive 2 SD Prec shocks	-0.786	-0.389
	(1.644)	(1.829)
Total No of Negative 1 SD Prec shocks	-1.112	-0.773
	(1.238)	(0.896)
Total No of Negative 2 SD Prec shocks	-14.696***	-23.713***
	(4.944)	(6.181)
Firm Size	-4.126***	-4.121***
	(0.211)	(0.506)
No of water shortages per day in a typical month		-7.960*
		(4.467)
Average duration of water shortage		-0.006
		(0.050)
Average Monthly Temp for the Year	1.677**	1.714**
	(0.709)	(0.685)
Square of Average Monthly Temp for the Year	-0.056***	-0.059***
	(0.022)	(0.022)
Constant	1.218	5.531
	(8.564)	(7.922)
Country Fixed Effects	YES	YES
Year Fixed Effects	YES	YES
Sector (2 digit) Fixed Effects	YES	YES
Number of observations	6,351	5,05

Note: Standard errors clustered following the design of the survey. ***: p<0.01, **: p<0.05, *: p<0.1:

These results relying on enterprise surveys present the advantage of being regional. The cost of this purely-cross section approach is that we rely on spatial variations only to identify an impact, making harder to control for unobserved firms' characteristics. We show that these regional results on droughts for firms remain true when using panel data for Brazil.

We construct a municipality-year panel recording the number of firms across Brazil using administrative data from the Annual Social Information Report (Relação Anual de Informações Sociais – RAIS). We access annual data between 2000 and 2013. Data being annual, we use the number of months with shocks during the year as our continuous drought variable as with SEDLAC and enterprise surveys. We estimate a fixed effect model as well as a dynamic fixed-effect model (Table A5.3). Using RAIS data, we find that even small shocks (both wet and dry) slowed down the general increase in the number of firms observed over the period in Brazil, even if the impact remains economically limited: an additional small shock is associated with a relative decrease in the number of firms by less than half percent. The effect is the largest for large dry shocks: an additional large dry shock during the year decreases the number of registered firms by about one percent to two percent. This impact is again four time large than the impact of large wet shocks.

These results are consistent with our main results using LABLAC and SEDLAC data. Together, they indicate an economy-wide impact of large shocks (the workers and the firms); particularly in the case of droughts. Several pathways could explain this economically significant and consistent negative impact of large dry shocks. We explore two of them in the following section to provide an economic rationale for these results.

Table A5.3 – A firms' perspective: shocks, employment growth and the creation of firms in Brazil using administrative data

	Nb of firms	Nb of firms - Dynamic Panel
Lag 1 - Nb Firms		0.703***
		-0.01
Small Negative Shocks	-0.004***	-0.001**
	-0.001	-0.001
Large Negative Shocks	-0.016***	-0.008**
	-0.006	-0.003
Small Positive Shocks	-0.003***	0.001
	-0.001	-0.001
Large Positive Shocks	0.003**	0.002**
	-0.002	-0.001
lnPOP_Total	0.368***	0.098***
	-0.03	-0.014
Avg Temperature	0.043**	0.045***
	-0.019	-0.01
Avg Temperature sq	-0.001*	-0.001***
	0	0
Constant	1.146***	0.124
	-0.338	-0.165
Observations	53,929	50,835
R-squared	0.359	0.639
City FE	Yes	Yes
Year FE	YES	YES
Number of municipalities	4,01	3,989

Robust standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1. Urban: Urban Pop > Rural Pop

A6: Who are the informal workers?

Table A6 – The profile of poor workers

	(1) LABLAC - Poor Less \$4	(2) LABLAC - Vulnerable Less \$10
Age	-0.0134***	-0.0234***
	(0.00152)	(0.00201)
Gender	-0.948***	-0.858***
	(0.0483)	(0.0410)
Head of Household (0/1)	-0.540***	-0.494***
	(0.0297)	(0.0194)
Years of Education	-0.313***	-0.465***
	(0.0168)	(0.0160)
Type of contrat (Baseline: Formal worker)		
Informal Worker	0.483***	0.493***
	(0.0726)	(0.0794)
Type of firm (Baseline: Large firm)		
Small Firm	1.162***	0.479***
	(0.113)	(0.0891)
Public Firm	-0.414***	-0.492***
	(0.109)	(0.0702)
Salaried Worker	0.153	0.690***
	(0.140)	(0.127)
Self-Employed	1.132***	1.099***
	(0.130)	(0.153)
Not Salaried	-1.505***	-3.169***
	(0.553)	(0.543)
Observations	11,085,836	11,085,836

Notes: We present evidence that being an informal worker is positively associated with the probability of being a poor or a vulnerable individual in the LABLAC data (based on \$4 and \$10 poverty lines). Results here are from a logit regression. Standard-errors are clustered at the city-level. Additional controls include year, city and sector 1 digit fixed effects, and a constant term. *** p<0.01, ** p<0.05, * p<0.1