Shocks in the Cities: The Economic Impact of Water Shocks in Latin American Metropolitan Areas

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Abstract

Water is key to economic activity. Unlike in rural areas, limited evidence exists on the impact of its natural variability in urban areas. In an increasingly urban world, this question matters as climate change promises to increase this variability. In this paper, we compile labor force surveys covering 13,000,000 workers living in 78 of the largest metropolitan areas of Latin America over 10 years, and enterprise surveys covering 6,300 firms, we construct exogenous rainfall variations and show that large rainfall variations (both wet and dry) negatively affect cities' labor market outcomes. The impact of droughts is four to six times larger than the impact of wet spells, and mainly affect informal workers. These results are robust to using household surveys from the region. We test three pathways: transmission of rural shocks to nearby cities, health consequences and fluctuations in electricity availability. The results accredit a city-specific vulnerability to water shocks.

"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

In 2014, 54 percent of the world's population lived in urban areas and by 2050 over 66 percent could be (UN-ESA 2014). As noted by Christiaensen and Kanbur (2017), not only is the overall geographic landscape changing dramatically, with many more people living in urban areas, the urban landscape itself is also undergoing significant changes. By 2025, close to 50 percent of the urban population in the developing world is predicted to live in cities of one million or more, compared to only 26.5 percent in 1970. With cities generating more than 80 percent of the global GDP, this changing pattern of urbanization has important implications for the reduction of poverty as it does for the policies and investments that can promote shared and sustainable growth.

Urban growth is a thirsty business and the rise in urbanization is projected to increase the demand for water from cities by 50 to 70 percent in coming years (2030 Water Group 2009). This demand is not only the result of a larger number of urban dwellers but also the result of more affluent and water intensive consumption patterns.

Water stress is already a major issue in many countries around the developed and developing world. As noted by McDonald, Weber, et al. (2014), one in four cities, representing US$4.2 trillion in economic activity, is water-stressed. [1] Even river basins with important reserves of freshwater such as in the south of Brazil have experienced important droughts in recent years. With global warming, water supply is expected to decrease in many parts of the world, particularly in the mid-latitudes (Norris et al. 2016). At the same time, rainfall variability will increase (Schellnhuber et al. 2013). Even with water infrastructure in place to manage water resources and demand, rainfall remains a core input of the water cycle, whether to replenish water reservoir or underground water. Incidentally, it remains a building block of water security.

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.

The role of water, the impact of excess or lack of rainfall in rural areas is at the center of an ever growing literature. It has been shown that the impact of extreme rainfall events harm economies that predominantly rely on agriculture as is the case in the majority of developing countries (Carleton and Hsiang 2016). However, evidence on how and how much rainfall and water availability matter in urban setting remains scarce. Some evidence is emerging on the harmful effect of floods in cities. They confirm an expected result that floods have a negative short-term effect on economic activity (Kocornik-Mina et al. 2015). The Intergovernmental Panel on Climate Change (IPCC) has also emphasized the negative impact of floods in cities, but has not addressed the potential risk associated to droughts.

Yet, there are good reasons to expect that droughts negatively impact cities. First, climate change increasingly exposes cities to the heightened impact of droughts as a result of the urban heat island effect (Oke 1982; Grimmond 2007; Li and Bou-Zeid 2013). Second, many water intensive activities such as manufacturing are located in metropolitan areas. These activities can be highly sensitive to water shortages. Third, cities rely on rural areas for their food supply. One might expect that rainfall shocks in a region will affect agricultural yields, which in turn can translate into an increase in food prices in the cities. Fourth, water is one of the principal inputs to produce electricity (Fthenakis and Kim 2010) and water scarcity in the region can lead to electric shutdowns as was recently seen in India or in São Paulo.[2] Fifth, the health literature points out the negative effects of droughts on health conditions as droughts increase the survival rate of vectors of diseases with water scarcity increasing the risk of diarrhea, and the risk of infection also rising with food shortages and malnutrition (Kovats et al. 2003). Cities' higher population density also favors the spread of diseases compared to rural areas, all the more so in the absence of adequate sanitation and sewerage. However, beyond stories and anecdotal evidence, to the best of our knowledge, there is no empirical evidence of the possible economic harm caused by droughts in urban areas.

This paper aims to fill this gap in the literature by studying the impact of rainfall shocks on labor outcomes (incomes, hours worked, employment dynamics) for workers and firms in the biggest metropolitan areas in Latin America countries. The focus on labor income is informed by its role as the principal channel through which economic growth has led to poverty reduction in the region for more than a decade. Even as growth trended downwards and even culminated in a contraction of regional economic activity in 2015 (Torre, Ize, Pienknagura, et al. 2015), the importance of la-

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

bor income in reducing poverty continued to increase (Calvo-Gonzalez et al. 2017). [3]

To analyze the impact of rainfall shocks on workers' labor outcomes, we compile different rounds of monthly harmonized labor force (LABLAC) between 2005 and 2014. Our dataset covers up to 13 million individuals living in around 80 cities from nine countries monthly. For firms, we compile Enterprise Surveys from 22 countries collected in 2010 covering a sample of more than 6,300 firms in Latin America and the Caribbean (LAC). Beyond data availability, several reasons motivate our focus on LAC. First, LAC is the one of the most urbanized region in the world, after North America (82 percent vs 80 percent) and above Europe (UN-ESA 2014). Second, the majority of the poor households in LAC live in urban areas (Vakis, Rigolini, and Lucchetti 2016). Third, several LAC countries are projected to be among the most severely water stressed countries in the world by 2040 (Luo, Young, and Reig 2015), and extreme rainfall events such as droughts and floods have occurred in the region recently. Third, with global warming, water availability should decrease in Latin America according to different scenarios, and the El Niño and la Niña phenomena will further aggravate extreme events.

We use a straightforward identification strategy to establish a causal impact of rainfall shocks on labor outcomes. Using global gridded weather data, we construct local monthly rainfall variations ("shocks") from the long run average precipitation of each city. By construction, these variations are exogenous. This exogeneity provides a quasi-natural experiment set-up for the analysis of a causal impact. We introduce several geographical and temporal fixed effects to control for unobservable characteristics. Outcomes in the cities during months of the same year but without shocks act as our counterfactual scenario.

Our results show that, at most, small precipitation shocks have only a limited impact on labor market outcomes in metropolitan areas, even when these small shocks recur frequently. However, large shocks (classified as very dry or very wet events by meteorologists) have an economically significant impact on labor market outcomes in urban areas. Both wet and dry large rainfall shocks negatively affect economic activity. Interestingly, we find consistent evidence that large dry shocks have a larger effect on the labor market of Latin American cities than large wet shocks. In our results, the economic harm caused by large dry shocks is four to six times larger than those caused by large wet shocks. Labor laws in Latin America countries appear to protect

3. f poverty reduction per year. Growth in all other income sources, including public transfers, accounted for less than one percentage point per year. During the slowdown (2012-2014), continued yet slowing growth in labor income accounts for practically all poverty reduction. This means that while labor income growth has slowed, its importance to poverty reduction has in fact grown.

formal workers from short-term shocks while informal workers are more exposed to shocks. [4] Labor legislation in Latin America is known to be rigid, even for OECD standards and the firing and hiring of formal workers is particularly difficult due to strong employment protection (Montenegro and Pagés 2004). In the formal sector however, our results show that firms respond to the consequences of large shocks at least by altering their hires decisions. We additionaly test the robustness of the results using harmonized household surveys (SEDLAC) available annually between 1992 and 2014.

We then analyze three potential pathways to understand the impacts. First, we test if rural shocks are transmitted to nearby cities through a general equilibrium mechanism (an increase of food prices or a decrease of demand driven by the decrease of rural incomes). To that end, we rely on structural equation models and gridded data on soils productivity. We do not find evidence supporting this channel. Second, we test whether rainfall shocks affect energy outages for firms using enterprises surveys for LAC. We find that large negative shocks are associated with an increase in power outages that could be the vector of a decrease in economic activity. Third, we test for the health consequences of rainfall shocks using a monthly panel of all hospital admissions in Brazil between 2000 and 2013. The results suggest that in metropolitan areas, shocks, and particularly large negative ones, are associated with worse health outcomes that could have consequences for labor markets.

Literature

The paper relates to three strands of the economic literature. The first pertains to cities, shocks and resilience; the second to labor markets in developing countries and shocks; and a third to the econometric literature on climate change.

The importance of water availability for agricultural productivity and thus rural income is self-evident. An important literature on the impact of rainfall shocks on agricultural activities exists showing that even shocks of a small amplitude can have important consequences on productivity. Decreases in productivity translate into an increase in poverty and negatively impacts key development outcomes such as health

4. For instance, In Brazil, under the 1988 Constitution, the country unemployment insurance provides that all involuntarily dismissed workers (from a formal job in the private sector, after at least six months of tenure) are eligible for three to five monthly payments (the maximum benefit duration based on the accumulated tenure over the three years prior to layoff). Benefit levels are based on the average wage in the three months before layoff, at replacement rates of 60–100 percent (World Bank 2016).

or education (Kazianga and Udry 2006; Dercon 2004; Hallegatte et al. 2016). The literature also documents the impact of rainfall variability on a number of outcomes such as agricultural wages in Bangladesh (Mueller and Quisumbing 2011), gender wage gap in agriculture in India (Mahajan 2017), land invasions in Brazil (Hidalgo et al. 2010), local tax revenues in Mali (Sanoh 2015) or even on farmers' stress level in Kenya (Chemin, De Laat, and Haushofer 2013). Similarly, the literature looking at the role of infrastructure related to water variability has focused on agriculture and rural areas as in the case of irrigation and dams (Duflo and Pande 2007) or rural-urban migration in sub-Saharan Africa (Barrios, Bertinelli, and Strobl 2006).

This strand of the research has also benefited from the expansion of the Climate-Economy Literature (Hsiang 2010; Hsiang 2016; Carleton and Hsiang 2016), which 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 panel of US daily temperature and individual data from the 2003-06 National Time Use Surveys to show that weather fluctuations 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).

In comparison, the literature for urban areas is much more limited in both breadth and depth. 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. At the household level, existing research has focused on rural-urban migration as the main transmission channel whether in Africa (Henderson, Storeygard, and Deichmann 2017) or in Brazil (Bastos, Busso, and Miller 2013). In that later case, the authors use five waves of census data combined with historical drought indexes and a difference-in-difference design. They find that an increase in drought frequency in the previous decade not only affects the agricultural sector (reduced value-added, employment and wages) but also lead to out-migration towards urban areas and thus long term effects on urban centers due to an accelerated sector reallocation.

Not surprisingly, the literature of the impact of shocks on urban labor markets is even more limited. A literature on large natural disasters (earthquakes, hurricanes and tropical storms) has emerged, showing mixed impacts. 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. Those results also echo those of Ahmed, Diffenbaugh, and Hertel (2009). Using a computable general equilibrium (CGE) simulation, the authors assess the poverty impacts of climate volatility for seven socio-economic groups in 16 developing countries. They find that extremes climate volatility increase poverty across their sample of developing countries particularly in Bangladesh, Mexico, Indonesia, and Africa. Poor urban workers are the most exposed. Since food is a major expenditure for those individuals, their overall consumption will fall with rising prices, pushing them below the poverty threshold.

Finally, narrowing on rainfall related shocks, Acevedo (2015) looks at labor markets in urban Colombia. She finds that a marginal effect of one additional extreme hydro-climatic event on labor supply and labor income is negative in the short term, with the effect of a negative hydro-climatic event larger for labor income than hours worked. Mueller and Osgood (2009) look at the impact of droughts on wages in Brazil between 1992 and 1995. While the authors find a negative impact of droughts on wages in rural areas, they are unable to confirm an impact in urban areas.

Our paper ties these strands of research, focusing on metropolitan regions in Latin America, a region among the most urbanized and best endowed in infrastructure among developing regions, in spite of its own infrastructure gap.[5] The focus on Latin America does not preclude a relevance of the analysis for other regions. In the case of Sub-Saharan Africa, urbanization has occurred at a much lower level of development than other regions, with an urbanization of people disjoint from the corresponding urbanization of capital (Lall, Henderson, and Venables 2017). In that context, the multi-faceted vulnerability of cities to large shocks and the high exposure of informal workers seen in Latin America have important implications for countries continents away.

The remainder of the paper is organized as follows. Section 2 describes the different datasets used in this analysis. Section 3 describes the empirical strategy and section 4 presents our main results on the impact of shocks. Section 5 analyzes path-

5. An upcoming World Bank report 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 (Fay et al. 2017)

ways. Section 6 discusses the findings and concludes.

2 Data

2.1 Workers: Labor force and Household surveys

We use the harmonized labor force surveys 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 surveys carried out in 24 Latin America and Caribbean countries since 2005. The sample of those surveys provides representative data for major metropolitan areas of subset of countries. We focus on these rounds of surveys representative of each metropolitan areas to conduct our analysis in an urban context. Our combined repeated cross-section dataset covers around 13,000,000 active occupied individuals living in 78 metropolitan areas from nine countries (Brazil, Chile, Colombia, El Salvador, Ecuador, Mexico, Paraguay, Peru, and Uruguay) monthly between 2005 and 2014. This sample is representative of a population of about 300,000,000 people, that is about half of the total Latin America population.

2.2 Firms: Enterprise Surveys

To study the impact of shocks on firms' hiring decisions, we compile Enterprise Surveys data from the World Bank. Enterprise Surveys contains data for formal manufacturing firms with five or more employees. These are all private firms – that is, no firm is fully government owned. 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. The sample for the analysis in this study covers 22 LAC countries and was collected in 2010 for which we have GPS coordinates of observations. 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. Table 1 summarizes the different rounds of surveys from LABLAC and Enterprise Surveys used in this paper.

Countries	LABLAC Monthly Data Nb. Cities	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 1 – Overview of the data

2.3 Weather

We use the weather data from 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, and with the GPS coordinates of the firms for the enterprise surveys (Figure 1).

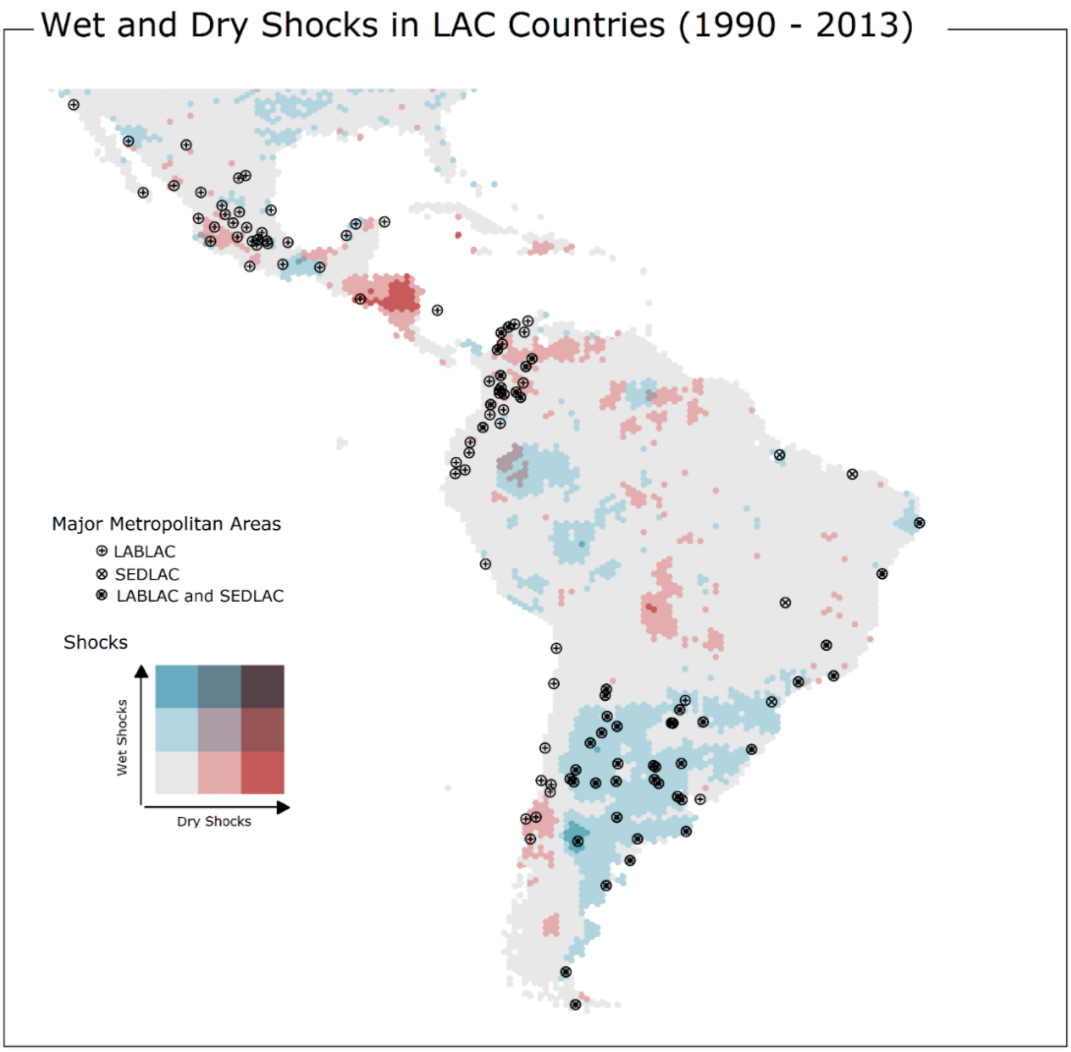

Figure 1 – Rainfall Shocks and Survey Data

3 Empirical Strategy

In this section, we present the empirical strategy used to study the impact of shocks on labor outcomes for workers and firms. We start by explaining the motivation behind the use of rainfall shocks instead of rainfall levels, and describe how these shocks are constructed. We then present the model estimated.

3.1 Precipitation shocks

We aim to measure the impact of water variability on incomes, on hours worked and on employment decisions. One of the empirical issues we face is that population dynamics which have led to urbanization have historical origins born out of deliberate choice to establish settlements and cities in locations where climate would have been most favorable to economic activity. This means that a correlation between current levels of economic activity and levels of rainfall could still exist, thereby preventing us from using the level of rainfall as an explanatory variable. We address this issue by focusing instead on local exogenous rainfall shocks.

We define shocks as follows: first, we calculate the long run mean and standard deviation between 1900 and 2014 of monthly precipitations for each gridcell for each month. We then construct small and large shocks in a given month-year/gridcell. A small shock is defined as a monthly rainfall that is one to two standard deviation away from the long run mean for that gridcell at that month. A large shock is defined as a two or more standard deviation of current rainfall from the long run mean for that gridcell at that month. We distinguish negative and positive deviations to obtain four types of shocks: small dry shocks ($1SD^-$ Shock), small wet shocks ($1SD^+$ Shock), large dry shocks ($2SD^-$ Shock) and large wet shocks ($2SD^+$).

Previous literature on rainfall shocks in rural settings mostly defines shocks using one standard deviation as a threshold and did not differentiate between $1SD$ and $2SD$ shocks (Maccini and Yang 2009; Rocha and Soares 2015). Yet, there are reasons to believe that damages resulting from $1SD$ and $2SD$ variations might be different, in particular for cities. A smaller $1SD$ shock can reasonably be expected to have an impact on agricultural yields, with little consequence on cities that are likely buffered by both infrastructure and the economic activity that is less sensitive to rainfall variations. Larger shocks are more likely to have an impact but the question of how much infrastructure buffers cities from larger shocks remains open.

Previous literature on rainfall shocks as well mostly uses annual data and look at the impact of abnormally dry and wet years. Using LABLAC, we are focusing on monthly shocks. Yet, what distinguishes wet shocks from dry shocks is the length of a typical event. On one hand, only few days of large wet deviations can cause floods or landslides, disturb activity and cause damages: wet shocks are usually short and only need to be short to have direct consequences. On the other hand, droughts are the results of sustained dry events. As a consequence, a dry event is unlikely to have an economic impact after only a month of negative deviation from its normal level. To take into account this difference between wet and dry spells with LABLAC, we create categorical variables of shocks. We split the shocks variables into three categories. The first categorie consists in abnormal deviations of rainfall over one month (the month contemporary to the recall period of the survey). The second one consists of abnormal deviations of rainfall over two months or more. Third as a control group, we have months with no deviation of rainfall.[6] For yearly enterprise surveys, we count the number of months with an abnormal dry or wet deviation during the given year.

These shocks – small and large - are by construction rare events. In our sample, about 8 percent of the individuals have been impacted by a monthly shock of one standard deviation on average over the period. Two and more standard deviations shocks are even rarer. Only 4.4 percent of our LABLAC sample was on average exposed to large positive shocks. 0.4 of the sample percent was exposed to large negative shocks.[7] The rarity of these shocks makes them hard to anticipate. Under this assumption, they are thus exogenous and our strategy provides us a quasi-natural experimental setting. Therefore, estimated coefficients represent the causal effect of rainfall shocks.

$2SD^+$ shocks correspond to the kind of rainfall shocks that would be expected to result in floods and landslides. In Latin America over the period covered by our study, $2SD^+$ 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.[8] It has also been the case in Argentina and in Brazil in 1992 and in 1997, and in Brazil in 2003 and 2004. Despite disrupting daily life and potentially economic activity, each $2SD^+$ shock has not resulted in important floods recorded by EM-DAT. As for large negative shocks, they capture events as the droughts that have hit Mexico in 2009, Colombia in 2010, as well as the first months of the long droughts that hit Belo Horizonte at the end of 2013 or Mexico at the end of 2014.

3.2 Rainfall, Incomes and Hours Worked

We specify our model as follows:

6. Only one city in LABLAC has experienced one three consecutive large shocks, forbidden us to create a fourth category.

7. In appendix A6, we use annual household surveys (SEDLAC) to test the robustness of our findings. In SEDLAC in a typical year, 1.4 months had a $1SD$ positive deviation, a figure that is similar for a $1SD$ negative deviation. A large positive shock occurs 0.58 times and a large negative shock month occurs 0.03 times per year.

8. 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.

$$ln(Income)_{i,j,m,y} = \alpha + \beta_1 1SD^{1+}_{j,m} + \beta_2 1SD^{2+}_{j,m} + \beta_3 1SD^{1-}_{j,m} + \beta_4 1SD^{2-}_{j,m}$$
$$+ \beta_5 2SD^{1+}_{j,m} + \beta_6 2SD^{2+}_{j,m} + \beta_7 2SD^{1-}_{j,m} + \beta_8 2SD^{2-}_{j,m} + \tau_1 Temperature_{j,m}$$
$$+ \tau_2 Temperature_{j,m-1} + \tau_3 Temperature^2_{j,m} + \tau_4 Temperature^2_{j,m-1} + \gamma_{j,y} + \mu_y + \epsilon_{i,j,m,y} \quad (1)$$

i denotes the individual, j the metropolitan area, m the month, y the year. Income represents the labor income earned during the month that precedes the survey. It is expressed in 2005 PPP. β_1 to β_8 are our coefficients of interests. They measure successively the impact of a one month small wet shock on contemporary incomes, of a two consecutive months small wet shock on incomes (contemporary and one month before), of a one month small dry shock on incomes, of a two consecutive months small dry shock on incomes, of a one month large wet shock on incomes, of a two consecutive months large wet shock on incomes, of a one month large shock on incomes, and of a two consecutive months large dry shock on incomes. We additionally study the impact of shocks on the number of hours worked by occupied respondents.

We control for temperatures (in C) and its squared value in the same period as the shocks (monthly temperatures up to two months before the survey in LABLAC). This matters as rainfall and temperatures are correlated (Auffhammer et al. 2013), and because temperature and economic activity have been shown to also be correlated (Hsiang 2010; Dell, Jones, and Olken 2012). We introduce year fixed effects μ_y to account for regional time varying characteristics, and cities-year fixed effects $\gamma_{j,y}$ to control for unobserved and time varying metropolitan characteristics. We hence use monthly rainfall variations during the same year y of the same city j to identify an impact of shocks on labor market outcomes. Finally, we cluster the standard error $\epsilon_{i,j,t}$ at the city-year level to account for the nested structure of the data (i.e. a respondent resides in a given metropolitan area and the metropolitan area is experiencing a shock).

In the different regressions, we estimate the model for all the active population, as well as for formal workers, informal workers, self-employed workers, workers from small firms and workers from large firms separately.[9] This subsample analysis is motivated by the hypothesis that informal workers should be more exposed to shocks than formal ones due to social policies and labor laws in Latin America.

9. 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) or if they are workers with a zero income.

3.3 Rainfall and firms' hiring decisions

Using enterprise surveys data, we specify our model as follows:

$$EmpGrowth_{i,k,j,r} = \alpha + \beta_1 1SD_j^+ + \beta_2 2SD_j^+ + \beta_3 1SD_j^- + \beta_4 2SD_j^- \\ + \tau_1 Temperature_j + \tau_2 Temperature_j^2 + \lambda ln(Size)_{i,j,r} + \gamma_{1,k} + \gamma_{2,r} + \epsilon_{i,j,k,r} \quad (2)$$

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.

4 Results

This section presents and discusses the econometric results. We start by looking at the impact of shocks on workers' incomes and hours worked. We then look at the impact of shocks of firms' hiring decisions.

4.1 Rainfall shocks and incomes

Table 2 shows the results for the impact of rainfall shocks on the logarithm of labor incomes using monthly labor force surveys. These results suggest that a rainfall shock (wet or dry) never has a positive impact on urban labor market outcomes. If small shocks rarely have an impact on labor incomes, large shocks consistently and substantially impact labor incomes, always negatively.

Indeed, we find that small wet rainfall shocks slightly decrease labor incomes of informal workers (-1.6 percent). Among them, self-employed are the most impacted (-2.6 percent). Self-employed also is the only subgroup to be impacted by small dry shocks: an abnormal dry month decreases labor incomes of self-employed by almost five percent.

As for large shocks, results in Table 2 suggest that large wet shocks are consistently associated with a decrease in labor incomes, at the exception of large firms. A two standard deviation of rainfall above the long run average decreases labor incomes by two to five percent. For large dry deviations, the occurrence of a single month of shock is not associated with decreases in incomes. However, sustained large dry periods (i.e., droughts) significantly affect the incomes of informal, self-employed workers from small firmsThe coefficient associated to these recurrent negative shocks is the largest of every shocks. The short-term negative impact experienced by informal, self-employed workers from small firms corresponds to a decrease in labor incomes of 13 to 14.5 percent. It then means that the harm caused by large dry shocks to workers are about six times larger than the harm caused by large wet shocks.

		(1) Active Pop	(2) Informal	(3) Formal	(4) Self Employed	(5) Large firms	(6) Small firms
Small Positive	1 Shock	-0.007	-0.016*	0.002	-0.026*	-0.006	-0.012
		(0.009)	(0.008)	(0.010)	(0.013)	(0.011)	(0.012)
	2 Shocks	0.004	0.018	0.002	0.013	0.005	0.021
		(0.007)	(0.017)	(0.006)	(0.023)	(0.005)	(0.019)
Small Negative	1 Shock	-0.012	-0.019	0.001	-0.049**	-0.002	-0.022
		(0.014)	(0.018)	(0.012)	(0.024)	(0.010)	(0.019)
	2 Shocks	-0.004	0.000	-0.013	-0.021	-0.029	-0.002
		(0.039)	(0.011)	(0.041)	(0.020)	(0.031)	(0.022)
Large Positive	1 Shock	-0.029*	-0.018	-0.049*	-0.007	-0.041	-0.043*
		(0.016)	(0.012)	(0.027)	(0.015)	(0.027)	(0.023)
	2 Shocks	-0.009	-0.021**	-0.002	-0.026**	-0.000	-0.023**
		(0.006)	(0.010)	(0.005)	(0.011)	(0.006)	(0.009)
Large Negative	1 Shock	-0.005	-0.000	0.002	-0.005	0.004	-0.004
		(0.016)	(0.015)	(0.012)	(0.018)	(0.015)	(0.021)
	2 Shocks	-0.104	-0.130**	-0.023	-0.137***	-0.033	-0.145***
		(0.064)	(0.055)	(0.032)	(0.050)	(0.028)	(0.036)
	Temperature m	-0.001	0.005	-0.001	-0.005	0.001	0.001
		(0.005)	(0.007)	(0.005)	(0.014)	(0.006)	(0.009)
	Temepratrure m-1	-0.001	-0.010	0.003	-0.007	0.005	-0.017*
		(0.005)	(0.010)	(0.007)	(0.010)	(0.007)	(0.009)
	Temperature m^2	0.000	-0.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Temepratrure $m\text{-}1^2$	-0.000	0.000	-0.000	0.000	-0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Constant	6.045***	5.639***	6.208***	5.807***	5.993***	5.820***
		(0.056)	(0.067)	(0.042)	(0.104)	(0.051)	(0.095)
	Observations	11,423,352	4,419,554	6,929,890	2,535,188	4,879,458	4,217,048
	R-squared	0.054	0.058	0.039	0.063	0.056	0.058
	City FE	YES	YES	YES	YES	YES	YES
	Year FE	YES	YES	YES	YES	YES	YES
	City - Year FE	YES	YES	YES	YES	YES	YES
	Clustered S.E.	City Year	City Year	City Year	City Year	City Year	City Year

Table 2 – The Short Term Impact of Rainfall Shocks on Labor Incomes

Results in Appendix A1 to A5 indicate that our findings are robust to several alternative specifications. In Table A1, we introduce a set of individual control variables. If by construction, shocks are exogenous and are not correlated with individual characteristics, not adding individual control variables in our main specification should not create an omitted variable bias. This is what we confirm here. The controls we add are the age of the respondent, gender, whether she/he is the household head, whether she/he is a formal worker and the sector (1 digit ISIC classification). The results remain unchanged for small shocks that are found to decrease the incomes of informal workers, and mainly self-employed ones. The results remain also the same for large wet shocks. For large dry shocks, the coefficient for the entire active population even becomes significant with individual controls: large dry shocks decrease labor incomes by seven percent in this specification. Not consistent with previous findings, large dry shocks are found to increase labor incomes for workers in formal firms. This finding for formal firms is however true only in this particular specification among the eight different ones we test.

In Table A2, we implement a more conservative clustering than in Table 2. Instead of the original city-year clustering, we cluster this time at the city level to consider potential time correlation of observations within cities. When doing that, the significance of our results remains unchanged. In Table A3, we adopt different time fixed effects to control for unobserved heterogeneity. On the left panel of Table A3, we add to our main specification global month fixed effect to control for seasonality in economic activity. It does not change our results. On the right panel of Table A3, we relax our specification by dropping the city-yeat fixed effect $\gamma_{j,y}$ and by using only a global year fixed effects μ_t and cities fixed effect γ_j. Once again, results remain quantitatively unchanged. Furthermore, because on shocks are by construction rare events, they only affect a small proportion of our cities. One could get worried that our LAC results are driven by what happens in a few cities only instead of representing a regional vulnerability of cities. In Figure A1, we run the regressions for our main results of large shocks for informal workers by dropping each time one city. If the results are driven by an outlier, the results should significantly lose in significance when we drop this observation. On the contrary, we show that our results are consistent over every single regressions.

In addition, we test the robustness of our results to an alternative measure of shocks. To be consistent with the economic literature, we have constructed our shocks variables based on the empirical long term distribution of local precipitations only (e.g., Maccini and Yang 2009; Rocha and Soares 2015; Mahajan 2017). Meteorologists have developed different indexes to track dry and wet spells. The Standard Precipitation Index (SPI) is one of the most popular index (McKee, Doesken, and Kleist 1993). We use the SPI approach to define alternative shocks. We computed a monthly SPI based on Willmott, Matsuura, and Legates (2001)'s data using the precincton package in R. We define thresholds of +/- 0.5 ("abnormally" to "moderately" dry/wet) and +/- 1.3 ("very"/ "severely" dry/wet) following the National Climatic Data Center classification to construct small and large shocks. We report the results in table A4. They confirm that large dry shocks negatively affect labor incomes. A sustained severe dry event decreases labor incomes, even for the whole population using SPI. Because the intensity of the shock differs from the one in the main specification, quantitative estimates differ. Severe dry shocks decerase labor incomes of the entire active populaton by three percent. As before, the point estimate for informal workers is larger than for formal workers, and the impact is the most severe for self-employed workers. For them, a severe droughts even during one month only is found to decrease labor incomes by 11 percent. For informal, self-employed and workers from small firms, both severe dry shocks over one and two months are found to negatively impact labor outcomes. If the point estimates associated with the coefficients for one month are larger than the point estimates for two months, these differences are not statistically significant. Interestingly, the expected results of a negative impact of large wet shocks previously found in all our specifications do not hold anymore with SPI. Very wet events measured by the SPI do not lead to any significant decrease in incomes, whatever the subgroup.

Finally, we show that are also results are robust to using a different dataset. The CEDLAS project in charge of LABLAC has also harmonized household surveys through the Socio-Economic Database for Latin America and the Caribbean (SEDLAC) initiative. Data are available annually since the early 1990s for some countries. We compile the rounds of surveys that are representative at the metropolitan area level to confirm our 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). This sample is representative this time of a population of about 80,000,000 active people.

SEDLAC being annual, 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. We display the results in Table A5. As opposed to our main specification, small wet shocks are associated with an increase in labor incomes. An additional small wet shock in a month increases labor incomes by 0.7 percent. This result is driven by informal workers. As before, small negative shocks are found to have no impact of labor outcomes while an additional large wet shock decreases labor incomes by a bit more than one percent. An additional large dry shock decreases labor incomes by more than four percent. Using annual data, the negative impact of large dry shocks is four times larger than the impact of large wet shocks.

In SEDLAC, non-labor incomes are consistently reported 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. And indeed, the right panel of Table A5 shows that for all small shocks and for large wet shocks, non-labor incomes do not vary following shocks. Non-labor

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

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, self-employed workers and small firms' 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.

To sum up, we find converging evidence that rainfall shocks harm urban workers through wages in LAC countries. Even moderate deviations from normal rainfall levels are found to negatively affect labor incomes even if the results are not consistent in every specifications. Particularly consistent is the negative impact of large shocks (both wet and dry) on labor incomes and the fact that large dry shocks are always four to six times more harmful than large wet shocks. Recalling that these large wet shocks are the ones that have lead to important floods in the region, this result can be seen as surprising. We continue the analysis by studying the impact of shocks on the number of hours worked.

4.2 Rainfall Shocks and the number of hours worked

Another pathway through which labor markets could adjust following a shock is in the number of hours worked. Results presented in Table 3 show that while the effect of small shocks is mixed, it is more consistent in the case of large shocks, especially consecutive ones.

Small wet shocks appear to have a positive impact on the number of hours worked: small in the case of a single shock and more marked in the case of consecutive shocks. Small dry shocks on the other hand would appear to have a negative impact for a single shock, notably in the case of small firms, the self-employed and informal workers, but a positive impact in the event of two consecutive small dry shocks. This could signal a strategy by those groups to compensate for a reduction of hours worked in the initial phase of the shock phase (captured under the one dry shock results).

Interestingly, large non-recurrent wet shocks affect primarily informal workers, the self-employed and small firms, whereas those non-recurrent one dry shocks do not appear to have such an impact on the number of hours worked for any group.

Both dry and wet consecutive large shocks lead to reductions of hours worked.

		(1)	(2)	(3)	(4)	(5)	(6)
		Active Pop	Informal	Formal	Self Employed	Large firms	Small firms
Small Positive	1 Shock	0.005	0.002	0.008**	-0.002	-0.002	0.008
		(0.004)	(0.002)	(0.004)	(0.008)	(0.004)	(0.007)
	2 Shocks	0.013	-0.002	0.009**	0.012	0.006	0.026
		(0.010)	(0.004)	(0.004)	(0.025)	(0.006)	(0.019)
Small Negative	1 Shock	-0.005	-0.005**	0.002	-0.037**	0.006	-0.017
		(0.007)	(0.002)	(0.006)	(0.019)	(0.009)	(0.011)
	2 Shocks	0.024***	-0.003	0.008*	0.018	0.000	0.045***
		(0.007)	(0.004)	(0.005)	(0.017)	(0.008)	(0.015)
Large Positive	1 Shock	-0.005	0.002	0.006	-0.039**	0.014	-0.021*
		(0.004)	(0.003)	(0.006)	(0.017)	(0.009)	(0.012)
	2 Shocks	-0.005**	-0.004	-0.000	-0.021**	-0.001	-0.012**
		(0.002)	(0.004)	(0.003)	(0.009)	(0.003)	(0.005)
Large Negative	1 Shock	-0.003	-0.004	-0.003	-0.008	-0.000	-0.000
		(0.010)	(0.010)	(0.007)	(0.012)	(0.007)	(0.013)
	2 Shocks	-0.048***	-0.059***	-0.009	-0.049	-0.036	-0.054***
		(0.013)	(0.019)	(0.018)	(0.033)	(0.036)	(0.010)
	Temperature t	0.007***	0.006***	0.001	0.025**	-0.001	0.016**
		(0.002)	(0.002)	(0.003)	(0.010)	(0.004)	(0.008)
	Temepratrure t-1	-0.004	0.003*	0.002	-0.023*	0.002	-0.010
		(0.004)	(0.002)	(0.001)	(0.012)	(0.002)	(0.010)
	Temperature t ^{2}	-0.000**	-0.000**	-0.000	-0.001*	0.000	-0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Temepratrure t-1 ^{2}	0.000	-0.000***	-0.000	0.001	-0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Constant	3.645***	3.533***	3.685***	3.606***	3.722***	3.535***
		(0.018)	(0.022)	(0.017)	(0.068)	(0.022)	(0.042)
	Observations	9,611,658	3,835,442	5,738,783	2,235,283	4,164,315	3,979,083
	R-squared	0.014	0.032	0.017	0.048	0.023	0.035
	City FE	YES	YES	YES	YES	YES	YES
	Year FE	YES	YES	YES	YES	YES	YES
	City - Year FE	YES	YES	YES	YES	YES	YES
	Clustered S.E.	City Year	City Year	City Year	City Year	City Year	City Year

Table 3 – The Short Term Impact of Rainfall Shocks on Hours Worked (LABLAC)

4.3 A differentiated impact on workers

Our results on incomes and on hours worked show that low rainfall variability could be positive for labor incomes unlike high rainfall variability. That is, having slightly more rainfall than average might be positive for labor incomes but that having too much or too little water is on the contrary harmful. Experiencing a drought can be significantly more harmful than experiencing a flood. One important difference between droughts and floods is that floods affect every household and worker in similar proportions. For droughts, the impact is differentiated: informal workers, by definition less protected by labor laws and social policies, are shown to be more exposed to shocks in the urban Latin America context.

This idea that aggregate shocks do not have a similar impact on all households echoes recent literature for the region. Fuente, Ortiz-Juarez, and Rodriguez-Castelan (2015) show that low-income households in four Latin America countries are more likely to report being effected by shocks, including storms, floods, landslides, droughts, crop plagues, and animal diseases than the rest of the population. The same paper shows that the impact of a natural disaster on dwelling losses in Mexico was two times more likely among poor households than among the middle class. In our study, informal and self-employed 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. Interestingly however, if we break the sample by level of wealth or by gender, we find little evidence that shocks heterogeneously affect individuals with different levels of wealth or of different gender. This leads us to believe that poorer households are more impacted by shocks such as droughts not because they are poorer, but because of labor market mechanisms and because social security nets do not protect them adequately against those events.

If the evidence of an impact of shocks for formal workers is less systematic than for informal workers, shocks do not affect the formal sector. In Latin America, social laws are particularly protective for (formal) workers. It is then unlikely that firms decrease their workers' wages. On the contrary, firms might support the cost by seeing their margins decreasing. We test this hypothesis in the next section.

4.4 Rainfall shocks and firms' hiring decisions

We use enterprise surveys for LAC to analyze the impact of rainfall shocks on employment growth in formal firms (Table 4). Consistent over specifications, results indicate that in the case of a small wet shock, 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 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.

	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:

Table 4 – Enterprise Surveys: Precipitation and Employment growth

At the opposite of LABLAC or SEDLAC results where we use time and spatial differences to control for unobservables, our identification strategy with the Enterprise Surveys is only based on spatial differences. In appendix A7, 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) to confirm the enterprise result on employment growth and shocks. The RAIS provides information on the number of formal firms in Brazil. We access annual data between 2000 and 2013. Data being annual, we count the number of months with shocks during the year and treat shocks as continuous variables as with enterprise surveys and with SEDLAC. We estimate a fixed effect model as well as a dynamic fixed-effect model. 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 three of them in the following section to provide an economic rationale for these results.

5 Pathways

We investigate three pathways that could drive the results: firstly, the transmission of rural shocks to urban areas through changes in prices or changes in incomes in rural areas, secondly, by impacting electricity provision and, thirdly, through environment-related health conditions.

5.1 A transmission of rural shocks to cities?

Agriculture continues to contribute substantially to the economic activity of LAC: over five percent of the region's GDP and up to seven to eight percent for countries such as Argentina or Peru according to the 2017 World Development Indicators. As the sector is highly sensitive to rainfall shocks, a slowdown of the activity in agriculture could have a broader impact on the economy, both through changes in food prices in the local market, or through a slowdown of the economy for areas that rely on agribusiness. We test here if rural shocks affect economic outcomes in nearby cities.

We use a gridded dataset of a satellite-based estimate of net primary production (NPP) of soils from MODIS images as a proxy for crop productivity.[11] More specifically, we use the annual MOD17A3 provided by the Numerical Terradynamic Simulation Group (NTSG) at the University of Montana (Turner et al. 2006) and available annually since 2000. We want to estimate the impact of NPP variations of croplands

11. NPP is a standard measure of soils' productivity in the economics literature (Strobl and Strobl 2011; Blanc and Strobl 2013; Blanc and Strobl 2014) and the remote sensing literature (Lobell et al. 2002; Heinsch et al. 2005; Turner et al. 2006; Zhang et al. 2008).

around metropolitan areas. We use the Global Land Cover 2000 (GLC2000) dataset to delimitate cropland areas. GLC2000 classifies land cover into 22 distinct land cover categories based on SPOT 4 images. We use the land cover categories "Cropland", "Mosaic of Cropland/Shrub or Herbaceous Cover" and "Mosaic of Cropland/Tree Cover/Other Natural Vegetation" to identify agricultural crop areas within our grid cells. For each metropolitan area, we then compute the average annual NPP over cropland in different radius around cities, going from a 0.5 degree (approx. 50km at the equator) to 2.5 degrees (approx. 250km at the equator).

To estimate the impact of NPP on labor market incomes, it would be tempting to add the measure of NPP on the right hand side of equation (1). However, rainfall shocks can simultaneously affect incomes directly and indirectly through NPP. With shocks and NPP on the right hand side of equation (1), it would then be impossible to identify the direct impact of shocks on the city economic activity, from the indirect impact through a NPP pathway.

Instead, we specify a simultaneous equations model as follows:

$$\begin{aligned}\Delta ln(NPP)_{j,t} = \alpha_1 + \beta_{1_1} 1SD^{+}_{j,t} + \beta_{2_1} 2SD^{+}_{j,t} + \beta_{3_1} 1SD^{-}_{j,t} + \beta_{4_1} 2SD^{-}_{j,t} \\ + \tau_1 Temperature_{j,t} + \tau_2 Temperature^2_{j,t} + \gamma Latitude_j + \epsilon_{j,t} \quad (3)\end{aligned}$$

$$\begin{aligned}ln(Incomes_{i,j,t}) = \alpha_2 + \kappa \Delta ln(NPP)_{j,t} + \beta_{1_2} 1SD^{+}_{j,t} + \beta_{2_2} 2SD^{+}_{j,t} + \beta_{3_2} 1SD^{-}_{j,t} + \beta_{4_2} 2SD^{-}_{j,t} \\ + \tau_3 Temperature_{j,t} + \tau_4 Temperature^2_{j,t} + \widetilde{\epsilon_{j,t}} \quad (4)\end{aligned}$$

Where $\Delta ln(NPP)_{j,t}$ denotes the log difference of NPP around the metropolitan area i during year t for different radii. In the first stage, we determine the impact of shocks on the variation of NPP, controlling for temperatures and latitudes.[12] In the second stage, we test whether the estimated changes in NPP from the first stage and the shocks impact annual incomes as reported in the SEDLAC data. Here again, standard errors are clustered at the city year level. The model is estimated using maximum likelihood.

12. Models with fixed effects were not converging. We control for the latitude of the centroid of the gridcell to account for geography of the data. Everything else being equal, it is anticipated that gridcells closer to the equator have a larger productivity than gridcells located far from the equator.

LABLAC data being monthly and NPP data being annual, it is hard to conduct a joint estimate using these two datasets.

Table 6 displays the results of the simultaneous equation model that studies the impact of rainfall shocks on NPP around cities, and the impact of shocks and of NPP changes on labor incomes in cities. We find evidence that rainfall shocks affect yields. Particularly, there is consistent evidence that droughts decrease yields, whatever the scale at which we study the variations of NPP (from less than 50km, to 250km). A dry shock experienced for an additional month during a given year decreases soil productivity by about one percent. Yet, in the second stage of our model, the fitted value of the change of NPP never impacts annual labor incomes within cities. The direct impact of large dry shocks on annual labor incomes remains significant. Without being too definitive, this result suggests that the important negative impact of droughts found on cities does not seem to be driven by changes in the agricultural sector but by dynamics that are specific to cities. Two additional city-specific pathways are explored in the next sub-sections.

	< 0.5 degree		< 1.5 degree		0.5 to 1.5 degree		< 2.5 degree		1.5 to 2.5 degree	
	(1)	(2)	(5)	(6)	(9)	(10)	(13)	(14)	(17)	(18)
	NPP	Income	NPP	Income	NPP	Income	NPP	Income	NPP	Income
Variation of NPP during the year		0.120		0.031		0.026		0.031		-0.002
		(0.159)		(0.110)		(0.100)		(0.105)		(0.074)
Small Positive Shocks	0.000	-0.007	0.004	-0.011	0.004	-0.010	0.004	-0.010	0.004	-0.012
	(0.003)	(0.009)	(0.005)	(0.010)	(0.005)	(0.010)	(0.005)	(0.010)	(0.010)	(0.010)
Large Positive Shocks	0.006*	-0.003	0.009	0.003	0.009	0.003	0.008	0.002	0.003	0.003
	(0.003)	(0.012)	(0.005)	(0.012)	(0.006)	(0.012)	(0.005)	(0.011)	(0.008)	(0.012)
Small Negative Shocks	-0.008***	0.004	-0.014***	0.002	-0.014***	0.002	-0.014***	0.002	-0.016***	0.001
	(0.002)	(0.010)	(0.003)	(0.009)	(0.004)	(0.009)	(0.003)	(0.009)	(0.004)	(0.009)
Large Negative Shocks	0.012	-0.318***	0.003	-0.258***	-0.003	-0.258***	-0.007	-0.259***	-0.070	-0.262***
	(0.017)	(0.083)	(0.034)	(0.046)	(0.039)	(0.046)	(0.037)	(0.046)	(0.090)	(0.046)
Average Temperature	-0.000	-0.030**	0.011	0.150***	0.011	0.150***	0.010	0.148***	0.008	0.153***
	(0.003)	(0.015)	(0.014)	(0.029)	(0.015)	(0.029)	(0.014)	(0.029)	(0.015)	(0.029)
Average Temperature sq	-0.000	-0.000	-0.000	-0.004***	-0.000	-0.004***	-0.000	-0.004***	-0.000	-0.004***
	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)	(0.000)	(0.001)
Year		0.032***		0.031***		0.031***		0.032***		0.032***
		(0.004)		(0.003)		(0.003)		(0.003)		(0.003)
Latitude	0.000		0.001*		0.001*		0.001**		0.001**	
	(0.000)		(0.000)		(0.000)		(0.000)		(0.000)	
Constant	0.016	-57.797***	-0.081	-58.196***	-0.075	-58.210***	-0.062	-58.601***	-0.021	-58.643***
	(0.030)	(7.172)	(0.138)	(6.848)	(0.140)	(6.846)	(0.131)	(6.700)	(0.144)	(6.776)
Observations	1,499,476	1,499,476	1,396,837	1,396,837	1,396,837	1,396,837	1,430,173	1,430,173	1,397,045	1,397,045
Clustered SE	City Year	City Year	City Year	City Year	City Year	City Year	City Year	City Year	City Year	City Year

Table 5 – Agricultural Pathway

5.2 Rainfall shocks and electricity provision

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.[13] When excessive rainfall are followed by floods or landslides, large wet shocks might also cause an increase in power outages because of the infrastructures damages.

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:

$$\begin{aligned} PowerOut_{i,j,k} = \alpha + \beta_1 1SD_j^+ + \beta_2 2SD_j^+ + \beta_3 1SD_j^- + \beta_4 2SD_j^- \\ + \tau_1 Temperature_j + \tau_2 Temperature_j^2 + \gamma_1 Country_k + \epsilon_{i,j} \end{aligned} \tag{5}$$

Where $PowerOut_{i,j}$ is the number of power outages experienced by firm i in region j from country k . Over the different specifications, we consistently find that large shocks increase the number of power outages in LAC, and that the impact of large dry shocks is three times larger than the impact of large wet shocks (Table 6). 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

13. 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).

LAC	No of electrical outages per day in a typical month
	coef/se
Firm owns or shares a generator Y:1 N:0	0.011*
	-0,006
Log of Total Precipitation for the Year	-0,001
	-0,004
Average Monthly Temp for the Year	0
	0
Total No of Positive 1 SD Prec shocks excluding 2 SD	0,002
	-0,003
Total No of Positive 2 SD Prec shocks	0.029***
	-0,007
Total No of Negative 1 SD Prec shocks excluding 2 SD	0,003
	-0,003
Total No of Negative 2 SD Prec shocks	0.070***
	-0,023
Constant	0,018
	-0,032
Sector (ISIC 2 digit) Fixed Effects	YES
Country Fixed Effects	YES
Number of observations	7 610
R2	0,238

Table 6 – Rainfall Shocks and Power Outages in LAC

5.3 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 low and less than 30 percent of wastewater 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).[14]

Incidentally, health ranks high in terms of the potential pathways through which

14. 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)

shocks may affect households and workers through a deterioration of the quality of their environment leading to 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) 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.[15] 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 at year t is larger than its rural population.

To estimate the impact of shocks on health outcomes, we use municipality fixed-effects and month-fixed effects to control for unobserved fixed characteristics and time variations. We additionally control for yearly population for each municipality. The model estimated is:

$$\begin{aligned} ln(Hospital\ Admissions)_{i,t} &= \alpha + \beta_1 1SD^{+}_{i,t} + \beta_2 2SD^{+}_{i,t} + \beta_3 1SD^{-}_{i,t} + \beta_4 2SD^{-}_{i,t} \\ &+ \tau_1 Temperature_i + \tau_2 Temperature_i^2 + \gamma ln(Population)_{i,t} + \gamma_i + \mu_t + \epsilon_{i,t} \quad (6) \end{aligned}$$

15. 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.

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 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 7). They confirm that shocks increase the number of hospital admissions in Brazil. Small positive shocks, as well as small and large negative shocks are significant. The effect of contemporary small shocks remains limited (0.5 percent increase). Yet, when the current month sees a large negative deviation, hospital admissions in Brazil increase by 5 percent.

As for diarrhea for children under two years old, results show an increase of cases of diarrhea regardless of the type of shock. Cases increase by 1 percent with small wet shocks, by 2 percent with large wet shocks, by 0.7 percent with small dry shocks and by 6 percent with large dry shocks. Our data thus confirm that shocks are indeed associated with a deterioration of health status in urban areas, particularly in the event of droughts thus giving credence to our hypothesis.

6 Discussion and Conclusion

In this paper, we have highlighted that cities' economies are sensitive to rainfall shocks in Latin America, and that, maybe surprisingly and so far undocumented, the impact of dry shocks on labor market outcomes is significantly larger than the impact of wet shocks. With droughts, labor incomes significantly decrease, particularly if one work in the informal sector, and firm hire less. 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.

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 (both wet and dry) that city infrastructure appears insufficient

	Brazil		Ecuador
	Hospital Admissions	Cases of diarrhea - Children < 5yo	Hospital Admissions
Small Positive Shock	0.005*	0.011***	-0.019
	(0.003)	(0.004)	(0.024)
Large Positive Shock	0.000	0.018***	-0.001
	(0.004)	(0.006)	(0.043)
Small Negative Shock	0.005*	0.007*	-0.019
	(0.003)	(0.004)	(0.014)
Large Negative Shock	0.051**	0.058*	0.132**
	(0.022)	(0.032)	(0.063)
Average Temperature	-0.010***	0.030***	0.001
	(0.003)	(0.004)	(0.024)
Average Temperature sq	-0.000	-0.001***	0.000
	(0.000)	(0.000)	(0.000)
Log Population	0.534***	0.601***	
	(0.012)	(0.016)	
Constant	-2.362***	-2.896***	1.937***
	(0.146)	(0.164)	(0.296)
Observations	551,744	473,115	100,468
Year-Month FE	YES	YES	YES
Municipality FE	YES	YES	YES
R-squared	0.161	0.152	0.107
Number of Municipalities	3,946	3,944	987

Note: For Ecuador, standard errors are clustered at the province level as muncipalities (parishes) share the same weather shocks from our gridded dataset. In Brazil, we focus on urban areas, defined as muncipalities with an urban population larger than a rural one. As we do not have have population data for Ecuador, results are presented for all municipalities.

Table 7 – Rainfall shocks and hospital admissions in Brazil and Ecuador

to buffer, even in one of the world best endowed middle income regions in terms of infrastructure.

We show that this vulnerability percolates to the household level and could be one of the key drivers of poverty in the region. A rough estimate of the costs of shocks puts the income loss at around $10 per worker in the case of a one-month large wet shock. For large dry shocks, the loss is roughly $40. While droughts have a larger impact, wet shocks have been more frequent than droughts in Latin America over the last 20 years. Our results show that both wet shocks and dry shocks matter to the welfare of urban dwellers. In a context, of economic slowdown for the region, the vulnerability of labor incomes - a key tenant of poverty reduction - to shocks is especially preoccupying.

One of the main differences between large wet shocks and large dry shocks in our analysis is that wet shocks affect everyone in similar proportion while droughts have a more targeted and more severe impact on informal workers, the self-employed and small firms. With informal workers most affected by those shocks, and with extreme events expected to increase with climate change, the results have important implications for the type of safety nets that can protect vulnerable groups that may not be eligible for traditional poverty-focused social protection programs.

The strong impact of large negative shocks 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 two areas needing further research. First, 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. While this issue of urban water infrastructure has been raised in the water resource management literature (2030 Water Group 2009), 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.

Second, 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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Table A1

		Individual Controls					
		(1)	(2)	(3)	(4)	(5)	(6)
		Active Pop	Informal	Formal	Self Employed	Large firms	Small firms
Small Positive	1 Shock	-0.001	-0.013*	0.008	-0.022*	-0.002	-0.003
		(0.005)	(0.008)	(0.007)	(0.013)	(0.007)	(0.010)
	2 Shocks	0.009	0.017	0.005	0.005	0.001	0.019
		(0.007)	(0.015)	(0.006)	(0.016)	(0.006)	(0.014)
Small Negative	1 Shock	-0.003	-0.012	0.004	-0.039*	0.004	-0.007
		(0.006)	(0.015)	(0.010)	(0.020)	(0.006)	(0.012)
	2 Shocks	0.006	0.002	0.009	-0.022	0.004	0.013
		(0.010)	(0.012)	(0.017)	(0.028)	(0.010)	(0.014)
Large Positive	1 Shock	-0.039*	-0.028*	-0.043*	-0.021	-0.032	-0.042*
		(0.021)	(0.015)	(0.026)	(0.025)	(0.026)	(0.022)
	2 Shocks	-0.008*	-0.014	-0.003	-0.015	-0.000	-0.015
		(0.004)	(0.009)	(0.004)	(0.011)	(0.004)	(0.009)
Large Negative	1 Shock	0.002	0.001	0.003	-0.010	0.003	-0.001
		(0.009)	(0.015)	(0.010)	(0.016)	(0.011)	(0.016)
	2 Shocks	-0.069**	-0.126**	0.044***	-0.137***	0.019	-0.125***
		(0.033)	(0.056)	(0.014)	(0.042)	(0.016)	(0.030)
	Temperature t	0.002	-0.000	0.004	-0.014	0.011**	-0.003
		(0.002)	(0.007)	(0.004)	(0.011)	(0.005)	(0.003)
	Temepratrure t-1	-0.006	-0.006	-0.004	0.001	-0.004	-0.008
		(0.005)	(0.008)	(0.006)	(0.010)	(0.004)	(0.011)
	Temperature t sq	-0.000	0.000	-0.000	0.000	-0.000*	0.000***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Temepratrure t-1 sq	0.000	0.000	0.000	-0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Age	0.008***	0.004***	0.014***	0.000	0.014***	0.001***
		(0.000)	(0.000)	(0.000)	(0.000)	(0.001)	(0.000)
	Gender	0.255***	0.449***	0.185***	0.460***	0.177***	0.367***
		(0.011)	(0.020)	(0.010)	(0.021)	(0.012)	(0.020)
	Household Head	0.214***		0.184***	0.273***	0.190***	0.234***
		(0.004)		(0.005)	(0.010)	(0.006)	(0.004)
	Education level (years)	0.204***	0.145***	0.225***	0.162***	0.237***	0.134***
		(0.006)	(0.008)	(0.004)	(0.012)	(0.005)	(0.009)
	Informal worker	-0.518***				-0.316***	-0.671***
		(0.012)				(0.025)	(0.020)
	Constant	4.933***	4.740***	4.710***	4.709***	4.599***	5.503***
		(0.048)	(0.075)	(0.053)	(0.079)	(0.071)	(0.088)
	Observations	11,282,954	4,391,167	6,895,750	2,521,185	4,852,763	4,184,429
	R-squared	0.393	0.178	0.331	0.231	0.366	0.287
	City FE	YES	YES	YES	YES	YES	YES
	Year FE	YES	YES	YES	YES	YES	YES
	City - Year FE	YES	YES	YES	YES	YES	YES
	Clustered S.E.	City Year	City Year	City Year	City Year	City Year	City Year

Table 8 – Individual Controls

Table A2

		(1) Active Pop	(2) Informal	(3) Formal	(4) Self Employed	(5) Large firms	(6) Small firms
Small Positive	1 Shock	-0.007	-0.016**	0.002	-0.026*	-0.006	-0.012*
		(0.007)	(0.007)	(0.005)	(0.014)	(0.008)	(0.007)
	2 Shocks	0.004	0.018	0.002	0.013	0.005	0.021
		(0.004)	(0.012)	(0.005)	(0.014)	(0.004)	(0.014)
Small Negative	1 Shock	-0.012*	-0.019	0.001	-0.049	-0.002	-0.022
		(0.007)	(0.017)	(0.015)	(0.040)	(0.012)	(0.014)
	2 Shocks	-0.004	0.000	-0.013	-0.021	-0.029	-0.002
		(0.042)	(0.012)	(0.044)	(0.025)	(0.025)	(0.019)
Large Positive	1 Shock	-0.029	-0.018*	-0.049	-0.007	-0.041	-0.043
		(0.020)	(0.010)	(0.037)	(0.007)	(0.038)	(0.030)
	2 Shocks	-0.009*	-0.021**	-0.002	-0.026**	-0.000	-0.023***
		(0.005)	(0.008)	(0.005)	(0.010)	(0.006)	(0.007)
Large Negative	1 Shock	-0.005	-0.000	0.002	-0.005	0.004	-0.004
		(0.012)	(0.010)	(0.014)	(0.013)	(0.016)	(0.014)
	2 Shocks	-0.104	-0.130**	-0.023	-0.137***	-0.033	-0.145***
		(0.065)	(0.055)	(0.032)	(0.051)	(0.028)	(0.035)
	Temperature t	-0.001	0.005	-0.001	-0.005	0.001	0.001
		(0.003)	(0.004)	(0.003)	(0.007)	(0.003)	(0.005)
	Temepratrure t-1	-0.001	-0.010	0.003	-0.007	0.005	-0.017
		(0.004)	(0.007)	(0.005)	(0.006)	(0.007)	(0.011)
	Temperature t sq	0.000	-0.000	0.000	0.000	0.000	0.000**
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Temepratrure t-1 sq	-0.000	0.000	-0.000	0.000	-0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Constant	6.045***	5.639***	6.208***	5.807***	5.993***	5.820***
		(0.045)	(0.038)	(0.046)	(0.104)	(0.051)	(0.095)
	Observations	11,423,352	4,419,554	6,929,890	2,535,188	4,879,458	4,217,048
	R-squared	0.054	0.058	0.039	0.063	0.056	0.058
	City FE	YES	YES	YES	YES	YES	YES
	Year FE	YES	YES	YES	YES	YES	YES
	City - Year FE	YES	YES	YES	YES	YES	YES
	Clustered S.E.	City	City	City	City	City	City

Table 9 – Alternative Clustering

Table A3

		City FE, Year FE, City-Year FE and Month FE						Year FE and City FE					
		Active Pop	Informal	Formal	Self Employed	Large firms	Small firms	Active Pop	Informal	Formal	Self Employed	Large firms	Small firms
Small Positive	1 Shock	-0.007	-0.017*	0.003	-0.029*	-0.007	-0.012	0.009	-0.000	0.014	0.001	0.006	0.007
		(0.009)	(0.009)	(0.009)	(0.015)	(0.011)	(0.011)	(0.010)	(0.011)	(0.010)	(0.017)	(0.011)	(0.013)
	2 Shocks	0.004	0.014	0.008	0.006	0.009	0.020	0.021	0.032	0.014	0.036	0.019*	0.040*
		(0.008)	(0.018)	(0.006)	(0.027)	(0.007)	(0.020)	(0.015)	(0.021)	(0.011)	(0.027)	(0.010)	(0.021)
Small Negative	1 Shock	-0.010	-0.017	0.002	-0.046**	-0.002	-0.018	-0.020	-0.021	-0.006	-0.046**	-0.010	-0.029*
		(0.014)	(0.018)	(0.012)	(0.023)	(0.010)	(0.018)	(0.014)	(0.016)	(0.012)	(0.020)	(0.011)	(0.017)
	2 Shocks	0.002	0.007	-0.001	-0.012	-0.018	0.006	0.018	0.022	0.012	0.003	-0.007	0.024
		(0.038)	(0.011)	(0.040)	(0.019)	(0.031)	(0.022)	(0.040)	(0.020)	(0.040)	(0.026)	(0.031)	(0.032)
Large Positive	1 Shock	-0.026	-0.016	-0.042*	-0.007	-0.033	-0.041*	-0.044***	-0.037**	-0.060**	-0.028*	-0.052**	-0.057**
		(0.016)	(0.012)	(0.023)	(0.017)	(0.024)	(0.022)	(0.016)	(0.014)	(0.026)	(0.016)	(0.026)	(0.024)
	2 Shocks	-0.009	-0.016	-0.011*	-0.018	-0.004	-0.022*	0.004	-0.002	0.003	0.004	-0.001	-0.004
		(0.007)	(0.012)	(0.006)	(0.015)	(0.008)	(0.012)	(0.023)	(0.030)	(0.017)	(0.034)	(0.017)	(0.026)
Large Negative	1 Shock	0.003	0.002	0.015	-0.002	0.016	0.003	-0.003	0.000	-0.000	-0.001	0.008	-0.009
		(0.017)	(0.018)	(0.014)	(0.021)	(0.015)	(0.023)	(0.020)	(0.021)	(0.017)	(0.023)	(0.017)	(0.023)
	2 Shocks	-0.086	-0.113**	0.001	-0.112**	-0.010	-0.122***	-0.082	-0.084*	-0.026	-0.097***	0.014	-0.112***
		(0.065)	(0.051)	(0.034)	(0.047)	(0.031)	(0.035)	(0.068)	(0.046)	(0.038)	(0.037)	(0.040)	(0.033)
	Temperature t	-0.001	0.007	0.000	0.000	0.002	0.001	-0.000	0.003	0.001	-0.012	-0.001	0.001
		(0.004)	(0.006)	(0.006)	(0.012)	(0.005)	(0.009)	(0.005)	(0.008)	(0.006)	(0.015)	(0.005)	(0.008)
	Temepratrure t-1	-0.002	-0.017**	0.003	-0.019**	0.008	-0.022***	0.001	-0.012	0.004	-0.006	0.007	-0.017*
		(0.005)	(0.008)	(0.007)	(0.008)	(0.007)	(0.008)	(0.005)	(0.008)	(0.007)	(0.008)	(0.007)	(0.009)
	Temperature t sq	0.000	-0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Temepratrure t-1 sq	-0.000	0.000	-0.000	0.000**	-0.000**	0.000*	-0.000	0.000	-0.000	0.000	-0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Constant	6.083***	5.705***	6.216***	5.923***	5.986***	5.894***	6.116***	5.809***	6.249***	5.989***	6.073***	5.915***
		(0.050)	(0.068)	(0.034)	(0.112)	(0.045)	(0.094)	(0.077)	(0.084)	(0.060)	(0.120)	(0.070)	(0.103)
	Observations	11,423,352	4,419,554	6,929,890	2,535,188	4,879,458	4,217,048	11,423,352	4,419,554	6,929,890	2,535,188	4,879,458	4,217,048
	R-squared	0.054	0.058	0.039	0.064	0.056	0.059	0.047	0.048	0.033	0.052	0.050	0.050
	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
	City - Year FE	YES	YES	YES	YES	YES	YES	No	No	No	No	No	No
	Month FE	YES	YES	YES	YES	YES	YES	No	No	No	No	No	No
	Clustered S.E.	City Year	City Year	City Year	City Year	City Year	City Year	City Year	City Year	City Year	City Year	City Year	City Year

Table 10 – Alternative Fixed Effects

Table A4

		(1)	(2)	(3)	(4)	(5)	(6)
		Active Pop	Informal	Formal	Self Employed	Large firms	Small firms
Small Positive	1 Shock	0.000	0.005	-0.006	-0.001	-0.006	0.002
		(0.010)	(0.011)	(0.007)	(0.018)	(0.006)	(0.016)
	2 Shocks	-0.018	0.010	-0.013	0.000	-0.030	-0.018*
		(0.019)	(0.015)	(0.024)	(0.011)	(0.022)	(0.011)
Small Negative	1 Shock	-0.011	-0.003	-0.005	-0.012	-0.014	0.002
		(0.009)	(0.011)	(0.014)	(0.020)	(0.012)	(0.017)
	2 Shocks	-0.007	-0.002	-0.004	-0.009	-0.003	-0.009
		(0.012)	(0.014)	(0.012)	(0.020)	(0.011)	(0.017)
Large Positive	1 Shock	-0.012	-0.009	-0.017	-0.006	-0.010	-0.021
		(0.009)	(0.008)	(0.013)	(0.011)	(0.014)	(0.015)
	2 Shocks	-0.003	0.001	-0.005	-0.008	-0.006	0.008
		(0.006)	(0.016)	(0.005)	(0.021)	(0.007)	(0.019)
Large Negative	1 Shock	-0.017	-0.047*	0.011	-0.110**	0.006	-0.054**
		(0.017)	(0.027)	(0.017)	(0.046)	(0.019)	(0.026)
	2 Shocks	-0.031***	-0.028**	-0.020*	-0.035**	-0.015	-0.031**
		(0.011)	(0.011)	(0.011)	(0.017)	(0.011)	(0.012)
	Temperature t	-0.001	0.005	-0.001	-0.004	0.002	0.001
		(0.006)	(0.008)	(0.005)	(0.015)	(0.005)	(0.010)
	Temepratrure t-1	-0.001	-0.010	0.002	-0.008	0.005	-0.019*
		(0.006)	(0.010)	(0.008)	(0.009)	(0.007)	(0.010)
	Temperature t sq	0.000	-0.000	0.000	0.000	0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Temepratrure t-1 sq	-0.000	0.000	-0.000	0.000	-0.000	0.000
		(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
	Constant	6.057***	5.653***	6.209***	5.829***	5.985***	5.846***
		(0.062)	(0.067)	(0.039)	(0.107)	(0.049)	(0.100)
	Observations	11,423,352	4,419,554	6,929,890	2,535,188	4,879,458	4,217,048
	R-squared	0.054	0.058	0.039	0.063	0.056	0.058
	City FE	YES	YES	YES	YES	YES	YES
	Year FE	YES	YES	YES	YES	YES	YES
	City - Year FE	YES	YES	YES	YES	YES	YES
	Clustered S.E.	City Year	City Year	City Year	City Year	City Year	City Year

Table 11 – SPI

Table A5

	Labor Income						Non-Labor Income					
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
	Active Pop	Informal	Formal	Self Employed	Large Firms	Small Firms	Active Pop	Informal	Formal	Self Employed	Large Firms	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 12 – SEDLAC

Table A6

	(1)	(2)
	LABLAC - Poor Less $4	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)
Constant	-2.282***	1.864***
	(0.175)	(0.233)
Year FE	YES	YES
City FE	YES	YES
Sectore ISIC 1 FE	YES	YES
Observations	11,085,836	11,085,836

In this table, we present evidence that being an informal worker, a self-employed worker or a worker in a small firm is positively associated with the probability of being a poor or a vulnerable individual (based on $4 and $10 poverty lines). Results here are from a logit regression. Standard-errors are clustered at the city-level. *** p<0.01, ** p<0.05, * p<0.1

Table 13 – The profile of poor workers

Table A7

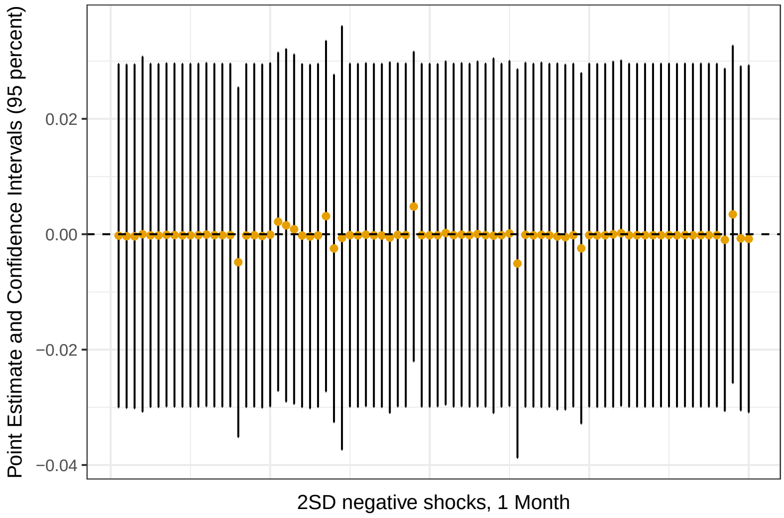
	Nb of firms	Nb of firms - Dynamic Panel
Lag 1 - Nb Firms		0.703***
		-0.01
Small Negative Shocks	-0.004***	-0.001**
	-0.001	-0.001
Large Negative Shocks	-0.016***	-0.008**
	-0.006	-0.003
Small Positive Shocks	-0.003***	0.001
	-0.001	-0.001
Large Positive Shocks	0.003**	0.002**
	-0.002	-0.001
lnPOP_Total	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

Table 14 – A firms' perspective: shocks, employment growth and the creation of firms in Brazil using administrative data

Figure A1

(a) 2 SD Negative Shocks for 1 Month



(b) 2 SD Negative Shocks for 2 Months

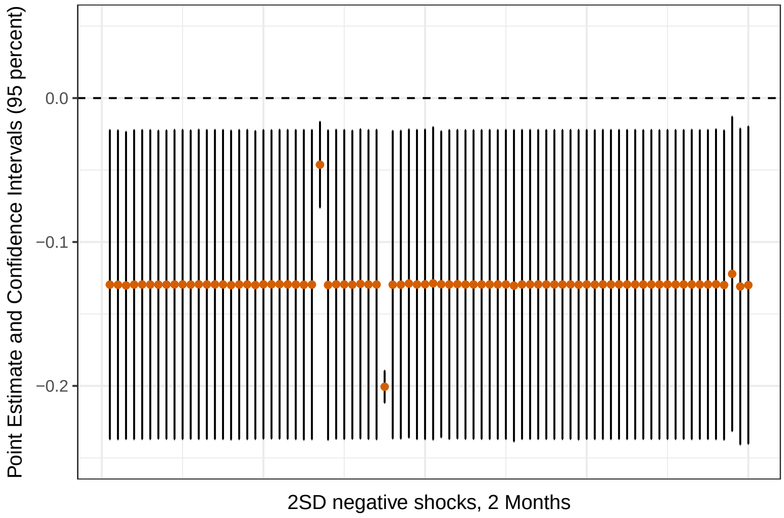
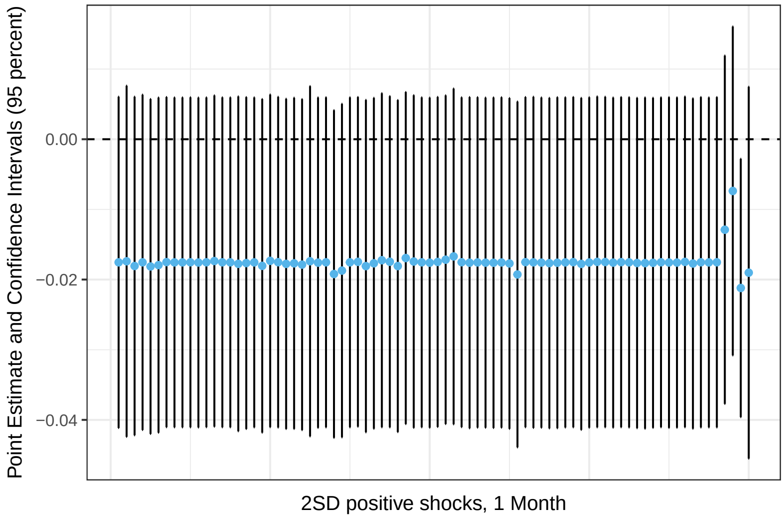


Figure .1 – Robustness: Dropping cities one by one, large dry shocks

(a) 2 SD Positive Shocks for 1 Month



(b) 2 SD Positive Shocks for 2 Months

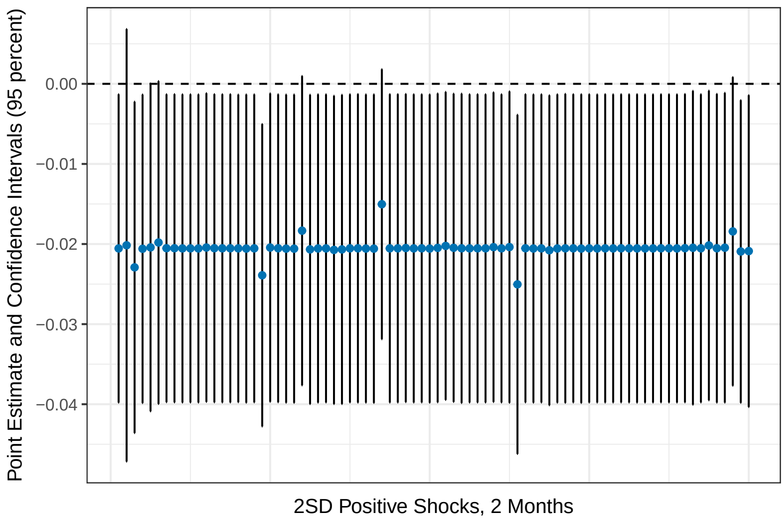


Figure .2 – Robustness: Dropping cities one by one, large wet shocks