Environment and Development Economics (2021), **26**, 450–465
doi:10.1017/S1355770X21000073

EDE

RESEARCH ARTICLE

Do temperature shocks affect non-agriculture wages in Brazil? Evidence from individual-level panel data

Jaqueline Oliveira,[1]* Bruno Palialol,[2] and Paula Pereda[2]

[1]Rhodes College, Memphis, TN, USA and [2]University of São Paulo, São Paulo, Brazil
*Corresponding author. oliveiraj@rhodes.edu

(Submitted 01 September 2019; revised 03 August 2020, 21 December 2020; accepted 21 January 2021; first published online 5 April 2021)

Abstract
The relationship between temperature and agriculture outcomes in Brazil has been widely explored, overlooking the fact that most of the country's labor force is employed in non-agriculture sectors. We use monthly individual-level panel data spanning the period from January 2015 to December 2016 to ask whether temperature shocks impact non-agriculture wages in formal labor markets. Our results show that additional days in a month that fall within high-temperature ranges have significant adverse effects on real wages. Assuming a uniform climate change scenario where the daily temperature distribution shifts by 2°C, we calculate income losses for formal workers in non-agriculture markets equivalent to 0.12 per cent of 2015 GDP.

Key words: climate change; temperature shocks; formal labor markets; labor productivity; non-agriculture sector; wages

JEL classification: C23; J24; Q54

1. Introduction

The link between temperature and economic outcomes in agricultural markets around the world and, in particular, in Brazil, has been the subject of much research.[1] But despite Brazil's agriculture sector being of great relevance for the country's economy, the majority of its population lives in urban areas, and most of the country's labor force

[1]Mendelsohn *et al.* (1994) and Schlenker *et al.* (2005) use cross-sectional data on land values to estimate climate effects on agriculture production. More recently, the literature uses panel data to identify temperature effects on agricultural profits/yields. See Deschenes and Greenstone (2007) and Schlenker and Roberts (2009) for U.S. and Schlenker and Lobell (2010), Feng *et al.* (2010), Welch *et al.* (2010), Chen *et al.* (2016) and Zhang *et al.* (2017) for developing countries. For studies which focus on the Brazilian context, see Assad *et al.* (2004), Sun *et al.* (2007), Barbarisi *et al.* (2007), Assad *et al.* (2013) and Silva *et al.* (2019) for weather effects on specific crops, and Massetti *et al.* (2013), Araújo *et al.* (2014), Pereda and Alves (2018), Castro *et al.* (2019) and Oliveira and Pereda (2020) for weather and climate effects on agricultural outcomes.

is employed in non-agriculture sectors.[2] A complete picture of the economic effects of temperature variations requires, therefore, the analysis of outcomes for those employed in non-agriculture activities. And yet, the empirical evidence on the existence and magnitude of such effects, especially using detailed individual-level data, is scant.[3] This study helps to fill in this gap.

In this paper, we analyze the effects of short-term temperature shocks on Brazil's non-agricultural labor markets. In particular, we focus on individual wages. To that end, we leverage rich data from administrative records covering the universe of Brazilian formal workers and their workplaces. After we draw a random sample from the universe, we end up with individual-level panel data on 209,350 workers for whom we observe monthly data on wages; hours worked; firm, sector and municipality of employment; and other labor market outcomes; spanning the period January 2015 through December 2016.[4] We then merge daily weather data to the panel using information on workers' municipality of employment.

We argue that our panel data analysis exploiting monthly variation in wages and daily temperature distribution presents important advantages. As we show in figure 1, there is considerable wage variation in our sample, both in nominal and real figures.[5] Thus, we would be missing much of the movement in wages that occurs within a year if we employed annual data instead. Furthermore, because we are interested in the short-term effects of temperature shocks, month-to-month variation in daily temperatures represents a more unexpected change to assess the consequences of extreme heat.[6] Finally, climate change is expected to increase unevenly across seasons in Brazil as winter temperatures might increase 1°C more than summer temperatures between 2070–2099.[7] The data, therefore, allow us to explore differential effects by month and understand future changes in weather at a finer level of disaggregation.

Our econometric approach is based on a specification where temperature effects are captured by the number of days in a month that falls in various temperature bins – following Deschenes and Greenstone (2011) – and worker, firm, municipality-month, and municipality-year fixed effects are included. We find that one additional day in a

[2]Data from Brazilian Household Survey (2019) and Population Census (2010) reveal that 84.4 per cent of Brazil's population lives in urban areas and 90 per cent of the labor force is employed in non-agriculture sectors.

[3]Dell *et al.* (2014) review the empirical evidence on non-agricultural outcomes, such as labor productivity, migration and human health. The focus of these studies is mostly on human health. Most studies assess the effects of cold and heat on mortality rates, mainly for infants and the elderly (Deschenes and Greenstone, 2011; Barreca *et al.*, 2015, 2016; Burgess *et al.*, 2017). See Deschenes (2014) for a review of the impacts of extreme temperatures on human health.

[4]We use 2015 and 2016 because these are the years when monthly wage data are available and can be matched to monthly weather data at the municipality level.

[5]Nearly 70 per cent of the month-to-month percentage change in wages is different from zero and, among non-zero changes, close to 80 per cent lies in the −21.2 to +30.7 per cent range.

[6]We acknowledge that several studies of weather effects on infant health normally use monthly or bi-monthly panel data (Barreca, 2012; Wilde *et al.*, 2017; Banerjee and Maharaj, 2020). Jacob *et al.* (2007) and Ranson (2014) explore monthly and weekly panels to investigate the weather (temperature and/or precipitation) effect on criminality rates in the United States.

[7]While summer temperatures might increase from 2.3 to 3.9°C between 2070–2099 depending on the Brazilian region, winter temperatures can rise from 3.3 to 4.9°C during the same period in the most pessimistic scenario. The calculations are based on CPTEC/INPE (Center for Weather Forecasting and Climate Studies of the National Institute for Space Research) forecasts for the A2 scenario by comparing the 2070–2099 average with the 1980–2010 average.

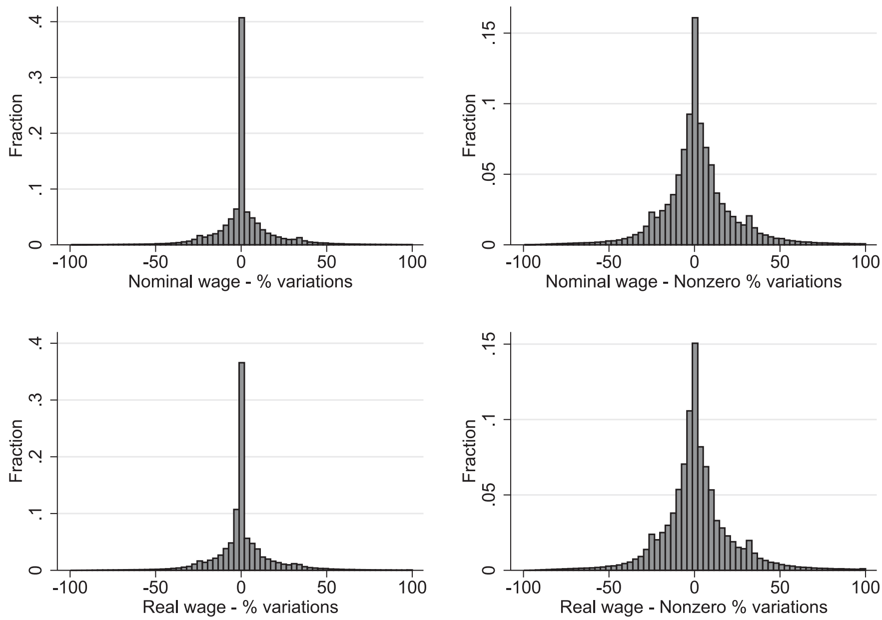

Figure 1. Percentage monthly variation in nominal and real wages.
Notes: The figure shows the distribution of percentage monthly changes in nominal and real wages for our estimating sample. We calculate changes between consecutive months only, ignoring missing values. The panels on the left include cases where percentage variation in nominal wages is zero, whereas the panels on the right exclude those cases. Data source: RAIS 2015–2016.

month where temperatures reach levels above 30°C – and one fewer day in the 18–21°C range – reduces real wages in formal labor markets by 0.2 per cent. Assuming a climate change scenario where daily temperatures rise uniformly by 2°C, we estimate annual income losses equivalent to 0.12 per cent of Brazil's 2015 GDP.

One concern we face is that weather shocks could have affected individuals' labor market mobility. If workers respond to temperature shocks by migrating out of their current municipality, changing sectors, or switching employers, any temperature-wage relationship estimated from municipality-level data could be reflecting changes in job types and labor force composition. Because our analysis exploits a rich panel data on individuals and firms, we can empirically check for this mechanism. We find little evidence that these transitions have a role in explaining our results.

This paper dialogues more directly with a vast literature that exploits short-term, mostly annual, weather changes to assess the broad impacts of temperature on agriculture outcomes (Deschenes and Greenstone, 2007; Schlenker and Roberts, 2009; Burke and Emerick, 2016; Chen *et al.*, 2016; Zhang *et al.*, 2017), county-level income (Deryugina and Hsiang, 2014), and country-level GDP (Hsiang, 2010; Dell *et al.*, 2012). We add to this body of knowledge by providing novel evidence of adverse effects on individual-level income from month-to-month increases in the incidence of days with extreme high temperatures. This paper also relates to a recent literature that investigates and finds links between extreme temperatures and workers' output in non-agriculture sectors of developing countries (Cai *et al.*, 2018; Somanathan *et al.*, 2018; Zhang *et al.*, 2018; Chen and

Yang, 2019; Adhvaryu *et al.*, 2020; Colmer, 2020), as well as a strand that studies wage adjustments to transitory economic and environmental shocks (Jayachandran, 2006; Franklin and Labonne, 2019; Kaur, 2019).[8]

Aside from this introduction, we structure the paper as follows. We describe the monthly wage and weather data in section 2. We outline our empirical strategy and discuss identification of temperature effects from individual-level panel data, as well as presenting the main results, in section 3. We discuss additional results and robustness checks in section 4. And finally, we offer some big-picture insights drawn from our results in section 5.

2. Wage and weather data

2.1. Employer-employee panel

We source worker-level data on monthly wages from the Annual Social Information Report (RAIS), which is an employer-employee administrative database covering 99 per cent of the formal labor force, starting in January 2015 and ending in December 2016.[9] We draw a random sample of the universe of workers and match them to weather data pertaining to the municipality (county) where they work. We further restrict our sample to workers aged 25 to 55 and exclude workers in agriculture, public administration and military occupations. Our final estimating sample has 3,468,613 worker-month observations representing 209,350 workers.[10]

We calculate hourly wages as the ratio between monthly wages and monthly hours of work in the main occupation.[11] To create a measure of real wages (base month-year is January 2015), we deflate nominal wages using the Brazilian official consumer price index by month, calculated by the Brazilian Institute of Geography and Statistics (IBGE).

Although our main focus is on the temperature-wage relationship, we exploit the relationship with other labor market outcomes that could complement our main findings: contractual hours worked per month, days on leave (in a given month) and type of employment contract (permanent versus temporary), as well as changes in firm, sector, and/or municipality of employment.

Table 1 presents descriptive statistics of workers from our estimating sample. The average worker makes, in real terms, about 12.40 Brazilian real (R$) per hour (US$3.10/hour) and has less than a high-school degree (11.44 years of schooling), revealing the relatively low-skill level of the workers in Brazil's formal labor markets.[12] From the descriptive statistics we also see that these workers are engaged in long-term contracts since as many as 98 per cent of the sample is employed in permanent jobs. The average worker is employed for an average of 43 hours per week; about 10 per cent of them missed at least one day of work in the 2015–2016 period.

Table 1 also shows numbers that characterize the panel dimension of the data. Data on wages are available for an average of 16.57 months (out of 24). Wages rose 5.92 times

[8]See also Dell *et al.* (2014), Deryugina and Hsiang (2014), Zivin and Neidell (2014), Barreca *et al.* (2016) and Behrer and Park (2017) for how climate change and weather impact other labor market outcomes.

[9]The panel starts in 2015 because it is the first year that RAIS provides monthly wage data. It ends in 2016 because the daily weather data are available up to that year. Also, RAIS 2016 presents imputation errors that we correct before using the data. The issue and correction procedure are detailed in online appendix B.

[10]For more details about the handling of employer-employee data, see online appendix B.

[11]The monthly wage includes labor income, tips, payment for performance, commission fees, additional gratifications from tenure, labor prizes, additional vacation pay, allowances of any kind, value-worked

Table 1. Sample of employees in the formal labor force

	Mean	Std. Dev.
General information		
Nominal hourly wages (BRL/hour)	13.49	17.57
Real hourly wages (BRL/hour – Jan, 2015)	12.40	16.10
Years of schooling	11.44	2.93
Contractual hours (per week)	42.72	3.48
Proportion of workers with a permanent job	0.98	
Proportion of workers that missed at least one work day	0.10	
Panel information		
Proportion of workers that changed municipality	0.03	
Proportion of workers that changed sector	0.04	
Proportion of workers that changed employer	0.08	
Average number of months with wage data	16.57	7.54
Average number of times wages rose	5.92	4.08
Average number of times wages fell	5.13	3.72
Total number of employees in the estimating sample	209,350	

Notes: The table presents summary statistics of selected variables calculated for the 209,350 workers in our estimating sample. Real hourly wages are in January 2015 figures. Data source: RAIS 2015–2016.

and fell 5.13 times on average over the course of 2015–2016. We also learn that in the two-year period only 3 per cent of workers changed municipalities, 4 per cent changed sector of employment, and 8 per cent switched employers. These low numbers are not surprising given the short time frame our study covers.

Because the vast majority of our sample of formal workers is employed in permanent jobs, it is reasonable to ask how much monthly wages vary within our two-year time span. Figure 1 shows the distribution of the percentage variation in nominal and real wages between consecutive months from January 2015 to December 2016. The panels on the left display all the data, while the panels on the right condition on there being a non-zero change in wages between consecutive months. We observe a spike around zero: 40 per cent of nominal wages do not change and 10 per cent change very little. Excluding zero changes (panels on right), the 10^{th} and 90^{th} percentiles of the distribution are -20.7 and 29.7 per cent respectively. These numbers demonstrate that there is a considerable amount of month-to-month variation in nominal wages. The variation in real wages is even larger because monthly inflation rates are always positive over the period we analyze.

We also note that only a small fraction of the workers in our estimating sample did not experience any changes in nominal wages within the 24-month period (4,612 or 2.2 per cent of the sample). And around 12.8 per cent of the workers (26,860) had their nominal wages change every month within the same period. The deflation of wages naturally

notice, overtime pay or premiums, premium for unhealthy services (even if temporary), food stamps, maternity/paternity leave wage and student scholarships.

[12]The exchange rate was 1BRL $\approx$ 0.25USD on December 31, 2015. Source: International Monetary Fund.

https://doi.org/10.1017/S1355770X21000073 Published online by Cambridge University Press

creates small variations in real wages even when nominal wages were constant, which explains a larger fraction of workers whose real wages changed every month.[13]

2.2. Monthly weather data

To calculate monthly temperature bins, we use daily weather data generated by Xavier *et al.* (2017).[14] The authors use historical weather observations collected from rain gauges and weather stations from the Instituto Nacional de Meteorologia, the Agência Nacional deÁguas, and the Departamento deÁguas e Energia Elétrica de São Paulo. Temperature is available for all Brazilian territory starting in January 1980 and ending in June 2017, and precipitation is available from January 1980 to December 2016. The spatial resolution is $0.25\times0.25^{\circ}$, resulting in 27,216 grids.

We convert grid-level data to municipality-level data as follows. For latitude-longitude pairs which fall inside a municipality's boundaries, we assign as the municipality weather the average weather variables for those grids. When latitude-longitude pairs do not belong to the municipality polygon, we attribute the closest grid to the municipality centroid within a 0.5° ($\sim$55 km) range. Using this procedure, we are able to assign weather data to 3,226 municipalities, representing 137 million people, or about 67 per cent of the country's population in 2015.[15] After we assign daily grid-level data to each municipality, we distribute daily temperature in eight bin categories, ranging from less than 12°C to more than 30°C in intervals of 3°C. We do the same for precipitation, but using nine bins (see section 3).

Table 2 presents summary statistics of daily temperatures and number of days in a month that fall within each of the eight temperature bins. We calculate these averages from our worker-month sample because that allows us to look at the average number of days in a month that a worker is exposed to a particular temperature range. As the numbers indicate, within a month a worker is exposed to an average of 0.35 days when temperatures are below 12°C and to 0.40 days when temperatures are above 30°C. Workers are most exposed to temperatures in the 24–27°C range – an average of 8.77 days a month.

We also present the averages in table 2 by macro-regions to highlight the extent of the spatial climate variability in Brazil.[16] The workers most exposed to lower temperature ranges are located in the South and Southeast; they are the ones contributing to the identification of wage effects in those temperature ranges. Indeed, the average number of days in temperature ranges below 18°C is zero for those residing in the North and Northeast. Analogously, those most exposed to higher temperatures live in the

[13]Online appendix table A1 presents the distribution of workers across the number of times wages changes between two consecutive months from January 2015 to December 2016.

[14]This study is an updated version of Xavier *et al.* (2016). The authors compare six different techniques of data interpolation by using data from 3,625 rain gauges (for rainfall) and 735 weather stations (for temperatures). They conclude that the inverse distance weighting and angular distance weighting interpolation techniques are the best way of interpolating stations/rain gauges to the whole Brazilian territory. We use the interpolated data that performed better in their tests.

[15]Our estimating sample covers 2,436 municipalities, and these 2,436 municipalities encompass around 130 million people (63 per cent of the country's population in 2015). Online appendix figure A1 shows that the distributions of monthly average temperatures among the 3,226 municipalities with available weather data and the 2,436 municipalities included in the estimating sample are similar.

[16]Since 1970 the IBGE divides the Brazilian territory into five macro-regions based on their physical, economic and urban characteristics: North, Northeast, Southeast, South and Midwest.

Table 2. Average of monthly number of days across eight temperature bins, Brazil and macro-regions

	Brazil		Midwest		North		Northeast		South		Southeast	
	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD	Mean	SD
Temperature (°C)	23.13	3.62	24.81	2.14	28.03	1.04	26.80	1.96	20.16	3.85	22.35	2.90
Bin 1: <12°C	0.35	1.64	0.02	0.19	0.00	0.00	0.00	0.00	1.76	3.62	0.13	0.65
Bin 2: 12–15°C	0.79	2.20	0.14	0.66	0.00	0.00	0.00	0.00	2.88	4.06	0.58	1.54
Bin 3: 15–18°C	2.46	4.34	0.31	1.00	0.00	0.04	0.00	0.01	4.96	5.13	2.95	4.62
Bin 4: 18–21°C	4.97	6.17	2.13	4.05	0.03	0.22	0.15	1.17	6.26	5.11	6.70	6.71
Bin 5: 21–24°C	7.61	7.28	8.01	8.05	0.20	0.78	3.55	7.54	7.49	6.02	9.22	6.95
Bin 6: 24–27°C	8.77	8.50	13.37	8.69	5.77	6.58	11.13	9.99	5.85	7.11	8.51	8.13
Bin 7: 27–30°C	5.10	8.65	6.05	7.78	22.24	7.15	13.97	11.62	1.25	3.03	2.31	5.09
Bin 8: >30°C	0.40	2.49	0.42	1.82	2.22	5.13	1.65	5.54	0.00	0.09	0.05	0.38

Notes: The table summarizes monthly average daily temperatures and the number of days in eight temperature bins spanning the months from January 2015 to December 2016. Averages are calculated based on the 3,468,613 worker-month observations employed in our estimations. This sample represents 2,436 Brazilian municipalities. Data source: RAIS 2015–2016 and Xavier *et al.* (2017), 2015–2016.

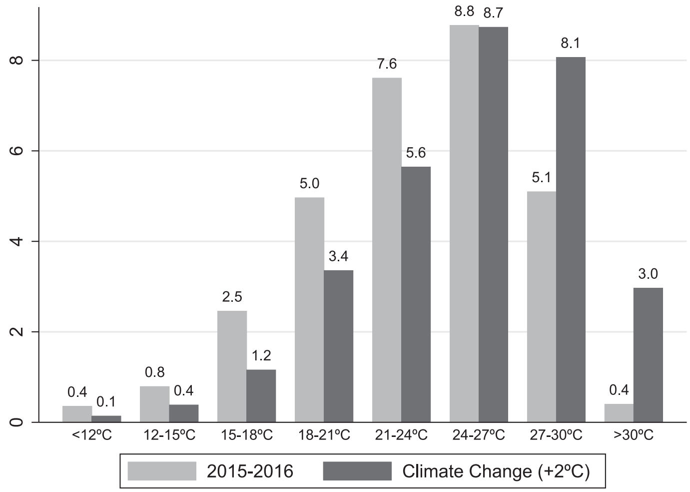

Figure 2. Average number of days in a month distributed across temperature bins, actual versus uniform climate change scenario.
Notes: The figure shows the average number of days in a month for each temperature bin observed in 2015–2016 (light shaded bars) and assuming a flat increase of +2°C across the entire distribution of daily weather to simulate uniform climate change. Averages are calculated from 3,468,613 worker-month observations employed in our estimations. Data source: RAIS 2015–2016 and Xavier *et al.* (2017), 2015–2016.

North and Northeast. For example, workers living in the North experience an average of 22 days a month when temperatures are in the 27–30°C range, and those in the Northeast, an average of 14 days in that range.

To get a sense of how future changes in climate may alter workers' exposure to days registering higher temperatures, we simulate the change in the average number of days in the various temperature bins assuming a uniform increase of 2°C in daily temperatures between 2015 and 2016. We present the simulated averages in figure 2. We see that individuals would experience an average of 2.6 additional days in a typical month when temperatures are above 30°C and 3.0 more days when temperatures reach levels between 27 and 30°C. Workers would be exposed to many fewer days with temperatures below 24°C.

3. Temperature shocks and formal sector wages

3.1. Empirical approach

To estimate the impact of short-term temperature changes on real wages, we adopt an approach based on temperature bins, first employed by Deschenes and Greenstone (2011). Because our estimation rests on month-to-month variation in temperature as an identifying source, we ultimately rely on the short-term weather unpredictability for causal inference.

We choose the bins specification below:

$$\log wage_{ifcmt} = \beta_0 + \sum_{j=1}^{8} \beta_j Temp^{j}_{cmt} + \sum_{h=1}^{9} \beta_h Rain^{h}_{cmt} + \alpha_i + \alpha_f + \alpha_{cm} + \alpha_{ct} + \epsilon_{ifcmt}, \tag{1}$$

https://doi.org/10.1017/S1355770X21000073 Published online by Cambridge University Press

where $wage_{ifcmt}$ is the real hourly wage of worker i employed by firm f located in municipality c in month m of year t; $Temp^{j}_{cmt}$ is the number of days in municipality c, month m of year t that fall in temperature bin j. $Rain^{h}_{cmt}$ is the number of days in municipality c, month m of year t that fall in precipitation bin h. We employ the following temperature bins: below 12°C; 12 to 15°C; 15 to 18°C; 18 to 21°C (base category); 21 to 24°C; 24 to 27°C; 27 to 30°C; and above 30°C.[17]

The remaining parameters, α_i, α_f, α_{cm} and α_{ct}, denote worker, firm, municipality-month, and municipality-year fixed effects, respectively; ϵ_{ifcmt} is the idiosyncratic error term. These fixed effects are key for identifying the short-term causal effects of temperature on wages. First, municipality-year fixed effects hold constant time-invariant municipality attributes, such as historical and cultural determinants of regional economic development, which are correlated with long-term climate; they also absorb annual shocks to local labor markets that are potentially associated with climate conditions. Municipality-month fixed effects are key to control for weather seasonality that may coincide with economic seasonality that causes labor markets to be more active. Individual fixed effects allow us to account for changes in workforce skill composition, both observed and unobserved, spurred by weather shocks within a municipality. Firm fixed effects help us control for firm-level unobservable characteristics such as endogenous adoption of climate-control technology, as well as changes in the sector/industry mix within a municipality.

3.2. Main results

We present the results in figure 3. Standard errors are clustered by economic region.[18] The coefficients on temperature bins lower than the base category (18–21°C), although negative, are not statistically discernible from the coefficient on the base category. We then conclude that there is no sizable impact on wages from an additional day that falls in those temperature ranges relative to the 18–21°C range. We do, however, find significant reductions in wages following increases in days that fall in temperature bins above the base category, and the higher the temperatures the higher the point estimates. Notably, the estimates indicate that one day in a month in the 27–30°C, and not in the 18–21°C range, leads to a 0.14 per cent reduction in real wages on average; the corresponding impact for the >30°C interval is a 0.2 per cent wage reduction.[19] This 0.2 per cent is equivalent to a loss of R$10.44 (US$2.61) in monthly income for the average worker.[20]

[17] For precipitation, we employ the following bins: 0mm; 0 to 0.05mm; 0.05 to 0.26mm; 0.26 to 0.8mm; 0.8 to 1.8mm; 1.8 to 3.6mm (base category); 3.6 to 6.7mm; 6.7 to 12.8mm; and above 12.8mm. We set the first precipitation bin to 0mm because around 21 per cent of the precipitation values in our sample are zero; we separate the other eight bins (to match temperature bins) so that every bin has approximately the same number of observations.

[18] IBGE classifies Brazilian municipalities according to their degree of economic influence, or poles of economic attraction (Região de Influencia das Cidades – REGIC). More details are available from this https://www.ibge.gov.br/geociencias/cartas-e-mapas/redes-geograficas/15798-regioes-de-influencia-das-cidades.html?=&t=o-que-e. We cluster the standard errors at the REGIC level.

[19] Studies based on annual fluctuations in weather find larger impacts on agriculture outcomes. For example, Schlenker and Roberts (2009) conclude that an additional day above 30°C leads to a 2 to 5 per cent decline in corn, soybeans and cotton yields in the U.S. Zhang *et al.* (2017) report even higher effects for rice, wheat and corn yield in China.

[20] The average worker makes 12.40 R$/hour and works 42.72 hours per week.

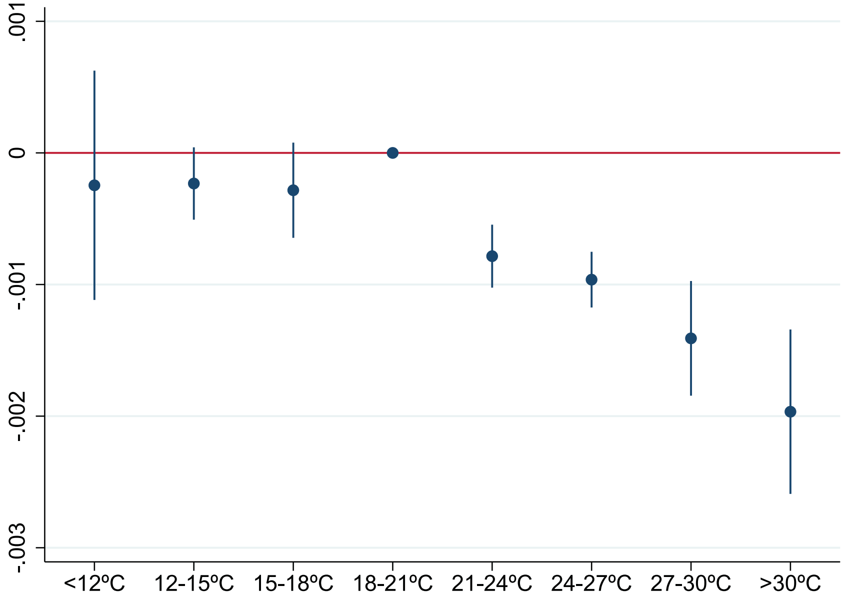

Figure 3. Short-term temperature shocks and real hourly wages.
Notes: The figure shows estimates from β coefficients in equation (1) and their 95 per cent confidence interval. We include worker, firm, municipality-month and municipality-year fixed effects, as well as precipitation bins. Temperature bins range from below 12°C to above 30°C in sets of 3°C. The 18–21°C bin is the base category. Standard errors are clustered by economic region. Online appendix table A2, column (1), shows the estimation results. Data sources: labor market data from RAIS 2015–2016 and weather data from Xavier *et al.* (2017).

We use our estimates to calculate the potential gains in formal sector wages if the daily temperature distribution in 2015 were replaced by that observed in the 1980–2009 period.[21] We estimate a 0.34 per cent gain in average annual wages which, considering the average annual wage of US$6,565.73 in our sample, amounts to nearly US$21.75 per worker. Given the size of the formal sector workforce, this figure adds up to US$1.26 billion in annual wage gains.

Our point estimates are in line with Chen and Yang (2019), whose analysis of annual firm-level data reveals a 0.21 per cent decline in Chinese industrial output from an additional day at 30°C relative to the 21–24°C range. They also compare to the findings reported in Deryugina and Hsiang (2014) based on annual county-level data for the U.S. – the authors report a 0.07 per cent reduction in annual net earnings per capita from an additional day above 30°C relative to the 21–24°C range. Our results show a 0.12 per cent reduction in hourly wages from an exchange of days between those temperature bins.

Finally, to arrive at a daily-productivity-loss figure, we follow the approach in Deryugina and Hsiang (2014).[22] Assuming that workers' labor incomes are distributed uniformly across 30 days within a month, each day of work would contribute 1/30 to

[21] Online appendix figure A2 shows the average number of days in each temperature bin for 2015 and 1980–2009.

[22] The authors estimate the impact of changes in daily temperature distribution on annual income per capita for U.S. counties.

https://doi.org/10.1017/S1355770X21000073 Published online by Cambridge University Press

monthly wages.[23] Then, a 0.2 per cent reduction in monthly labor income from an additional day in the $>30°$C range implies that day is nearly 6 per cent less productive than an average day. Assuming a linear effect above 20°C – the midpoint of the omitted bin category – yields a marginal effect in daily productivity of $-0.6\%/°$C. This is smaller than the $-1.7\%/°$C effect obtained from annual county-level income data for the U.S. (Deryugina and Hsiang, 2014), and the $-1.0\%/°$C and $-2.5\%/°$C from annual country-level GDP data for low and middle-income countries (Hsiang, 2010; Dell *et al.*, 2012). It is worth noting, however, that these differences are expected since our estimates are obtained from worker-level data and only represent the formal sector of the Brazilian economy.[24]

3.3. Climate change

In this subsection, we use our estimates from figure 3 to perform back-of-the-envelope calculations assuming that daily temperatures have uniformly increased by 2°C to reflect climate change predictions (Guivarch and Hallegatte, 2013; Kwok *et al.*, 2018).

To that end, we compute the predicted change in the number of days in each temperature bin for each municipality (see figure 2) and multiply the change by the estimated coefficient of the corresponding bin. We then impute this change in wages to the observed real wages of each individual in our estimating sample for each month of the year 2015 and sum it across all individuals. Under this flat 2°C-increase scenario, average annual wages would be 0.87 per cent lower compared to what prevails in 2015.[25] Extrapolating the losses to the universe of formal workers, we arrive at a R$8.44 billion loss in annual labor income – equivalent to US$2.17 billion. This figure corresponds to 0.12 per cent of 2015 GDP.

To assess regional differences, we consider the same exercise but now separate the sample in two: (i) The North, which encompasses the North and Northeast macro-regions; and (ii) The Center-South, which includes the Midwest, the South and the Southeast macro-regions.[26] We conclude that the effects are even greater among the warmest and least developed Northern regions: while formal sector workers in the North would lose 1.2 per cent of their monthly wages assuming a uniform increase of 2°C in temperatures, workers from the Center-South would lose 0.8 per cent.

4. Other labor market outcomes

We turn to a potentially relevant mechanism leading to wage effects from temperature shocks: jobs and labor force composition. Most analyses based on data aggregated at the county or municipality level do not deal with the possibility that weather shocks alter

[23] We show in online appendix figure A3 that we obtain virtually the same coefficients if we estimate equation (1) using the log of monthly salaries/wages instead of the log of hourly wages.

[24] Furthermore, as noted in Deryugina and Hsiang (2014), the country-level impacts reported in Hsiang (2010) and Dell *et al.* (2012) are estimated from variations in annual average temperatures. This variation likely yields stronger responses.

[25] To arrive at monthly figures for each worker, we calculate the effect on the hourly wages for each month of 2015 and multiply the change by the number of hours the individual worked in that month. We then add it across all months and workers to obtain an annual figure.

[26] The Northern regions are closer to the Equator and are, therefore, the warmest. They also happen to be the most socially vulnerable places. The Center-South regions, on the other hand, are less warm and more economically developed. Online appendix figures A4 and A5 show the monthly averages of days distributed across temperature bins for each of the two samples.

Table 3. Impact of temperature on labor market movements

	(1) Municipality	(2) Sector	(3) Firm
$<12°C$	0.00006 (0.00007)	0.00016*** (0.00003)	0.00015 (0.00010)
12–15°C	−0.00002 (0.00006)	0.00009** (0.00004)	−0.00001 (0.00008)
15–18°C	0.00000 (0.00007)	0.00003 (0.00003)	0.00002 (0.00009)
21–24°C	0.00000 (0.00006)	0.00002 (0.00003)	0.00010 (0.00009)
24–27°C	−0.00001 (0.00004)	0.00002 (0.00002)	0.00013** (0.00006)
27–30°C	0.00001 (0.00010)	0.00002 (0.00004)	0.00015 (0.00011)
$>30°C$	−0.00004 (0.00008)	−0.00003 (0.00004)	0.00012 (0.00011)
Obs.	3,200,675	3,200,675	3,200,675
Workers	201,544	201,544	201,544
Mean of dep. var.	0.20%	0.24%	0.53%

Notes: 'Municipality' is an indicator for whether the worker changes municipalities; 'Sector' is an indicator for changing sector of employment; and 'Firm' is an indicator for changing firms. Temperature bins range from below 12°C to above 30°C in sets of 3°C. The 18–21°C bin is the base category. We use our preferred specification, which includes worker, firm, municipality-month and municipality-year fixed effects. All regressions also include precipitation bins as controls and standard errors are clustered by economic region. Data sources: labor market data from RAIS 2015–2016 and weather data from Xavier *et al.* (2017). *p*-values: ** $p<0.05$, *** $p<0.01$.

the types of jobs and workers that are observed in a given locality at a certain period of time, especially studies relying on annual data where economic agents have more time to adapt to changes. If individuals react to environmental shocks by migrating in and out of localities, or switching jobs and sectors, an empirical relationship between wages and temperature may not be attributed to causal direct productivity impacts only, but also to changes in workforce skill composition, both observed and unobserved, or sectoral mix.

Because we have a uniquely rich panel of workers and observe them as they change municipality, sector or firm, we examine further if temperature shocks lead to such changes. We employ the same econometric approach used to estimate equation (1). In table 3, we present the results for three outcomes: an indicator for whether the individual has changed municipalities; an indicator for whether they have changed sector of employment; and another for whether they have changed firms.[27]

Some low-temperature bins in column (2) regarding effects on sector of employment are positive and significant; these cannot be reconciled with our baseline results, however, because we do not find significant impact on real wages at those temperature ranges. At the same time, the coefficients on the high-temperature bins are almost all

[27] 'Municipality', 'Sector' and 'Firm' are indicators for whether the worker's municipality, sector or firm in the current month is different from that in the previous month. Note that the sample size is slightly smaller because the indicators refer to changes relative to the previous month. This means that we lose data on the first month a worker is observed in the sample.

https://doi.org/10.1017/S1355770X21000073 Published online by Cambridge University Press

insignificant, the only exception being the coefficient associated with the 24–27°C bin in column (3). The lack of systematic movements in the labor market is expected given that our results only capture responses to very short-term changes in temperature. Case in point, as displayed in table 1, the percentage of workers that changed sector or firm at any time within the period we study is small (4 and 8 per cent respectively).[28]

To further investigate the issue, online appendix table A2, column (2), shows estimates obtained after removing from the sample those workers that have changed municipality, firm or sector at any time during the period of analysis. The coefficients are similar to those from the baseline, suggesting that these transitions are unlikely to drive our results. Finally, in appendix table A2 we compare our main estimates (column (1)) to estimates removing firm and worker fixed effects (column (3)). The comparison reveals that while the point estimates without these fixed effects are larger for high-temperature bins, we cannot reject that they are statistically similar to the baseline based on the estimated standard errors.

Next, we ask whether we see evidence that short-term temperature shocks lead to impacts on other measurable labor market outcomes that could be mediating the effects we find on hourly wages. From the RAIS dataset we are able to estimate versions of equation (1) using as outcomes hours of work, an indicator for days on leave, and an indicator for permanent employment contracts.[29] Table 4 presents the new set of results. From column (1) we see no significant effects of temperature on hours worked.[30] And while the coefficients on some temperature bins are statistically significant in column (3), their magnitudes are very small considering that 98 per cent of the workers held a permanent job. The estimates for days on leave presented in column (2) point to a slight increase in the likelihood a worker will be on leave of absence when the incidence of days hotter than 30°C goes up relative to days in the 18–21°C range. More specifically, an additional day above 30°C raises the likelihood by 0.035 percentage points. This corresponds to a 2 per cent increase in the incidence of leave of absence based on worker-month observations, suggesting that part of what we observe for wages could be explained by workers losing days of work.[31]

5. Final remarks

This paper employs worker-level panel data and exploits monthly variations in weather to study whether and how wages respond to short-term temperature shocks that potentially affect workers' productivity. We find that temperature plays an important role in formal, mostly non-agriculture, labor markets. Relative to the daily temperature distribution observed in the period 1980–2009, we estimate average annual wage losses of US$1.26 billion in 2015 for the universe of Brazilian formal sector workers.

[28] These percentages refer to the sample of workers, whereas the smaller percentages presented in table 3 are based on the worker-month observations.

[29] 'Log hours' is the log of contractual working hours, that is, the number of hours hired per week. 'Days on leave' is an indicator for whether the worker was on leave of absence in a given month. It is calculated from information on the start and end date of any leave of absence requested within the 2015–2016 period. It is worth noting that around 80 per cent of those leaves were requested because of accidents or disease. Finally, 'Permanent' is an indicator for whether the worker is under a permanent employment contract (zero if temporary).

[30] Online appendix figure A3 displays our baseline specification using the log of monthly real wages/salaries as the dependent variable. We find no difference from the baseline results using hourly real wages, which also corroborates that our results are not driven by changes in hours worked.

[31] We do not see a corresponding impact on hours, likely because those are contractual working hours and, therefore, less responsive to short-term shocks.

Table 4. Impact of temperature on employment outcomes

	(1)	(2)	(3)
	Log hours	I(Days on leave>0)	Permanent
<12°C	0.00000 (0.00001)	0.00018 (0.00013)	0.00001 (0.00001)
12–15°C	−0.00001 (0.00001)	0.00007 (0.00008)	0.00000 (0.00001)
15–18°C	0.00000 (0.00000)	0.00015** (0.00007)	−0.00000 (0.00001)
21–24°C	−0.00001 (0.00001)	−0.00001 (0.00004)	−0.00001 (0.00000)
24–27°C	−0.00000 (0.00000)	0.00006 (0.00005)	−0.00001** (0.00000)
27–30°C	−0.00000 (0.00001)	0.00011* (0.00007)	−0.00000 (0.00001)
>30°C	0.00001 (0.00001)	0.00035** (0.00014)	−0.00001 (0.00001)
Obs.	3,468,613	3,468,613	3,468,613
Workers	209,350	209,350	209,350
Mean of dep. var.	3.75	1.7%	98.5%

Notes: 'Log hours' is the log of contractual working hours; 'I(Days on leave>0)' is an indicator for whether the worker is on leave of absence; and 'Permanent' job is an indicator for whether the worker is in a permanent contract (zero, if temporary). We include worker, firm, municipality-month and municipality-year fixed effects, as well as precipitation bins. Temperature bins range from below 12°C to above 30°C in sets of 3°C. The 18–21°C bin is the base category. Standard errors are clustered by economic region. Data sources: labor market data from RAIS 2015–2016 and weather data from Xavier *et al.* (2017). *p*-values: * $p<0.10$, ** $p<0.05$.

We are able to draw some relevant insights from our analysis. Because Brazil's warmer North and Northeast regions are the poorest, weather vulnerability might deepen the existing south-north inequality. We calculate that workers from Northern Brazil could lose 1.2 per cent of their labor income when faced with uniform temperature increases of 2°C, while Southern workers could lose 0.8 per cent.

It is worth noting that because of data limitations, our analysis is restricted to formal-sector workers, leaving out around 40 per cent of Brazil's labor force that is employed in the informal sector. We believe, however, that this omission leads us to understate the adverse wage effects of elevated temperature, as informal workers are likely to be more vulnerable to weather shocks.

Supplementary material. The supplementary material for this article can be found at https://doi.org/10.1017/S1355770X21000073.

Acknowledgments. We are indebted to two anonymous referees for their invaluable comments and suggestions. Special thanks to The Regional and Urban Economics Lab (NEREUS) at the University of São Paulo for providing access to the their server. Any errors are our own.

References

Adhvaryu A, Kala N and Nyshadham A (2020) The light and the heat: productivity co-benefits of energy-saving technology. *Review of Economics and Statistics* **102**, 779–792.

Araújo PHC, Silva FDF, Gomes MFM, Féres JG and Braga MJ (2014) An analysis of the impact of climate change on agricultural productivity of Northeast of Brazil. *Rev. Econ. NE* **45**, 46–57.

Assad ED, Pinto HS, Zullo J, Maria A and Ávila H (2004) Climatic changes impact in agroclimatic zoning of coffee in Brazil. *Pesquisa Agropecuria Brasileira* **39**, 1057–1064.

Assad ED, Martins SC, Beltrão NEdM, Pinto HS (2013) Impacts of climate change on the agricultural zoning of climate risk for cotton cultivation in Brazil. *Pesquisa Agropecria Brasileira* **48**, 1–8.

Banerjee R and Maharaj R (2020) Heat, infant mortality, and adaptation: evidence from india. *Journal of Development Economics* **143**, 102378.

Barbarisi B, Marin FR, Assad ED, Pilau FG and Pacheco L (2007) Efeito das mudanças climáticas sobre a aptidão climática para cana-de-açúcar no estado de Goiás. Paper presented at the *XV Congresso Brasileiro de Agrometeorologia* 2-5 June 2007, Aracajú. SBA: Embrapa Tabuleiros Costeiros. pp. 1–5.

Barreca AI (2012) Climate change, humidity, and mortality in the united states. *Journal of Environmental Economics and Management* **63**, 19–34.

Barreca A, Clay K, Deschênes O, Greenstone M and Shapiro JS (2015) Convergence in adaptation to climate change: evidence from high temperatures and mortality, 1900–2004. *American Economic Review* **105**, 247–251.

Barreca A, Clay K, Deschenes O, Greenstone M and Shapiro JS (2016) Adapting to climate change: the remarkable decline in the us temperature-mortality relationship over the twentieth century. *Journal of Political Economy* **124**, 105–159.

Behrer AP and Park J (2017) Will we adapt? temperature, labor and adaptation to climate change. Harvard Project on Climate Agreements Working Papers.

Burgess R, Deschenes O, Donaldson D and Greenstone M (2017) Weather, climate change and death in india. Working Paper.

Burke M and Emerick K (2016) Adaptation to climate change: evidence from US agriculture. *American Economic Journal: Economic Policy* **8**, 106–140.

Cai X, Lu Y and Wang J (2018) The impact of temperature on manufacturing worker productivity: evidence from personnel data. *Journal of Comparative Economics* **46**, 889–905.

Castro NR, Spolador HFS and Marin FR (2019) Assessing the economy–climate relationships for brazilian agriculture. *Empirical Economics* **59**, 1161–1188.

Chen X and Yang L (2019) Temperature and industrial output: firm-level evidence from China. *Journal of Environmental Economics and Management* **95**, 257–274.

Chen S, Chen X and Xu J (2016) Impacts of climate change on agriculture: evidence from china. *Journal of Environmental Economics and Management* **76**, 105–124.

Colmer J (2020) Temperature, labor reallocation and industrial production: evidencefrom india. Centre for Economic Performance, London School of Economics and Political Science Discussion Paper No 1544.

Dell M, Jones BF and Olken BA (2012) Temperature shocks and economic growth: evidence from the last half century. *American Economic Journal: Macroeconomics* **4**, 66–95.

Dell M, Jones BF and Olken BA (2014) What do we learn from the weather? The new climate–economy literature. *Journal of Economic Literature* **52**, 740–798.

Deryugina T and Hsiang SM (2014) Does the environment still matter? Daily temperature and income in the United States. NBER Working Paper 20750, National Bureau of Economic Research.

Deschenes O (2014) Temperature, human health, and adaptation: a review of the empirical literature. *Energy Economics* **46**, 606–619.

Deschenes O and Greenstone M (2007) The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *The American Economic Review* **97**, 354–385.

Deschenes O and Greenstone M (2011) Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the US. *American Economic Journal: Applied Economics* **3**, 152–185.

Feng S, Krueger AB and Oppenheimer M (2010) Linkages among climate change, crop yields and Mexico–US cross-border migration. *Proceedings of the National Academy of Sciences* **107**, 14257–14262.

Franklin S and Labonne J (2019) Economic shocks and labor market flexibility. *Journal of Human Resources* **54**, 171–199.

Guivarch C and Hallegatte S (2013) 2c or not 2c? *Global Environmental Change* **23**, 179–192.

Hsiang SM (2010) Temperatures and cyclones strongly associated with economic production in the Caribbean and Central America. *Proceedings of the National Academy of Sciences* **107**, 15367–15372.

https://doi.org/10.1017/S1355770X21000073 Published online by Cambridge University Press

Jacob B, Lefgren L and Moretti E (2007) The dynamics of criminal behavior evidence from weather shocks. *Journal of Human Resources* **42**, 489–527.

Jayachandran S (2006) Selling labor low: wage responses to productivity shocks in developing countries. *Journal of Political Economy* **114**, 538–575.

Kaur S (2019) Nominal wage rigidity in village labor markets. *American Economic Review* **109**, 3585–3616.

Kwok TF, Xu Y, Liu X and Leung Y (2018) The impacts of economic structure on china's carbon dioxide emissions: an analysis with reference to other east asian economies. *Climate Policy* **18**, 1235–1245.

Massetti E, Guiducci RdCN, de Oliveira AF and Mendelsohn R (2013) The impact of climate change on the Brazilian agriculture: a Ricardian study at microregion level. *CMCC* **RP0200**, 1–31.

Mendelsohn R, Nordhaus WD and Shaw D (1994) The impact of global warming on agriculture: a Ricardian analysis. *The American Economic Review* **84**, 753–771.

Oliveira J and Pereda P (2020) The impact of climate change on internal migration in brazil. *Journal of Environmental Economics and Management* **103**, 102340.

Pereda PC and Alves D (2018) Climate and weather impacts on agriculture: the case of brazil. *Economia Aplicada* **22**, 5–26.

Ranson M (2014) Crime, weather, and climate change. *Journal of Environmental Economics and Management* **67**, 274–302.

Schlenker W and Lobell DB (2010) Robust negative impacts of climate change on African agriculture. *Environmental Research Letters* **5**, 014010.

Schlenker W and Roberts MJ (2009) Nonlinear temperature effects indicate severe damages to U.S. crop yields under climate change. *Proceedings of the National Academy of Sciences* **106**, 15594–15598.

Schlenker W, Hanemann WM and Fisher AC (2005) Will U.S. agriculture really benefit from global warming? Accounting for irrigation in the hedonic approach. *The American Economic Review* **95**, 395–406.

Silva WKdM, Freitas GP, Junior LMC, Pinto PALdA and Abrahão R (2019) Effects of climate change on sugarcane production in the state of Paraíba (Brazil): a panel data approach (1990-2015). *Climatic Change* **154**, 195–209.

Somanathan E, Somanathan R, Sudarshan A and Tewari M (2018) The impact of temperature on productivity and labor supply: evidence from Indian manufacturing. Working Paper, p. 70.

Sun L, Li H and Ward MN (2007) Climate variability and corn yields in semiarid Ceará, Brazil. *Journal of Applied Meteorology and Climatology* **46**, 226–240.

Welch JR, Vincent JR, Auffhammer M, Moya PF and Dobermann A (2010) Rice yields in tropical/subtropical Asia exhibit large but opposing sensitivities to minimum and maximum temperatures. *Proceedings of the National Academy of Sciences* **107**, 1452–14567.

Wilde J, Apouey BH and Jung T (2017) The effect of ambient temperature shocks during conception and early pregnancy on later life outcomes. *European Economic Review* **97**, 87–107.

Xavier AC, King CW and Scanlon BR (2016) Daily gridded meteorological variables in Brazil (1980–2013). *International Journal of Climatology* **36**, 2644–2659.

Xavier AC, King CW and Scanlon BR (2017) An update of Xavier, King and Scanlon (2016) daily precipitation gridded data set for the Brazil. *Proceedings of the Simpósio Brasileiro de Sensoriamento Remoto (SBSR)* **XVIII**, 562–569.

Zhang P, Zhang J and Chen M (2017) Economic impacts of climate change on agriculture: the importance of additional climatic variables other than temperature and precipitation. *Journal of Environmental Economics and Management* **83**, 8–31.

Zhang P, Deschenes O, Meng K and Zhang J (2018) Temperature effects on productivity and factor reallocation: evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management* **88**, 1–17.

Zivin J and Neidell M (2014) Temperature and the allocation of time: implications for climate change. *Journal of Labor Economics* **32**, 1–26.

Cite this article: Oliveira J, Palialol B, Pereda P (2021). Do temperature shocks affect non-agriculture wages in Brazil? Evidence from individual-level panel data. *Environment and Development Economics* **26**, 450–465. https://doi.org/10.1017/S1355770X21000073