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

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**Online Appendix** 

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# Appendix A. Figures and Tables



Figure A1. Temperature distribution.

*Notes:* The solid line depicts the distribution of monthly average temperatures for the 3,226 municipalities for which daily weather data are available. The dashed line shows the distribution of monthly average temperatures for the 2,436 municipalities that are represented in the estimating sample. The monthly average temperatures span the years 2015 and 2016. Data source: Xavier *et al.* (2017), 2015-2016.



Figure A2. Average number of days in a month distributed across temperature bins, 2015 vs. 1980-2009.

*Notes:* The figure shows the average number of days in a month for each temperature bin observed in 2015 (light shaded bar) and for average temperature bin observed from 1980-2009 (dark grey). Averages are calculated from 3,468,613 worker-month observations employed in our estimations. Data sources: RAIS 2015-2016 and weather data from Xavier *et al.* (2017).



Figure A3. Short-term temperature shocks on monthly real wages.

*Notes:* The figure shows estimates from equation (1) and the 95% confidence interval using monthly real wages as the dependent variable. We include worker, firm, municipality-month and municipality-year fixed effects, as well as precipitation bins as controls. Standard errors are clustered by economic region. Data sources: RAIS 2015-2016 and weather data from Xavier *et al.* (2017).



Figure A4. Monthly averages of days distributed across temperature bins, actual vs. uniform climate change scenario - North of Brazil.

Notes: The figure shows, only for the North and Northeast macro-regions of Brazil, the average number of days in a month for each temperature bin observed in 2015-2016 (light shaded bar) and assuming a flat increase of  $+2^{\circ}$ 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.



Figure A5. Monthly averages of days distributed across temperature bins, actual vs. uniform climate change scenario - Center-South of Brazil.

Notes: The figure shows, only for the Midwest, Southeast and South regions of Brazil, the average number of days in a month for each temperature bin observed in 2015-2016 (light shaded bar) and assuming a flat increase of  $+2^{\circ}$ 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 sources: RAIS 2015-2016 and weather data from Xavier *et al.* (2017).

	N	ominal W	ages	Real Wages					
	Obs.	Mean	Std. Dev.	Obs.	Mean	Std. Dev.			
0	4,612	1,495.0	1,821.8	236	2,295.9	4,938.1			
1	$13,\!547$	1,610.9	1,932.6	7,063	1,513.4	1,623.0			
2	12,598	1,712.5	2,315.2	7,089	1,600.1	2,040.8			
3	11,960	1,740.2	2,044.5	$6,\!688$	1,609.2	1,784.2			
4	11,213	1,848.2	2,219.8	5,910	1,649.8	2,087.7			
5	11,399	1,895.8	2,225.1	5,751	1,592.4	1,431.7			
6	11,033	1,966.3	2,153.4	5,733	$1,\!689.0$	1,869.4			
7	10,591	2,073.1	2,353.0	5,382	$1,\!652.2$	1,789.3			
8	9,690	2,161.3	2,568.3	5,132	1,620.5	1,474.1			
9	9,051	2,352.6	2,898.1	5,381	1,722.8	1,684.4			
10	8,333	2,369.7	2,724.9	5,007	$1,\!699.4$	1,644.8			
11	10,088	2,479.1	2,905.2	13,829	2,141.8	2,690.0			
12	6,535	2,447.8	2,789.4	5,786	1,760.0	1,657.6			
13	5,925	$2,\!459.2$	2,793.0	5,666	1,712.9	1,611.5			
14	5,510	2,419.4	$2,\!609.7$	5,760	1,734.7	$1,\!695.4$			
15	$5,\!119$	2,385.1	2,568.9	5,733	1,726.8	1,629.1			
16	4,891	$2,\!456.6$	2,693.0	5,884	1,785.6	2,008.9			
17	4,938	$2,\!481.9$	$2,\!636.5$	5,822	1,814.6	2,046.6			
18	4,494	2,447.4	2,520.3	$5,\!186$	1,816.0	1,764.6			
19	4,481	2,442.5	2,291.2	$5,\!147$	1,873.7	1,972.3			
20	4,802	2,563.0	$2,\!495.3$	4,980	1,866.9	1,760.5			
21	5,506	2,562.8	2,414.1	6,242	1,889.2	1,943.7			
22	$6,\!174$	$2,\!657.0$	2,542.1	$3,\!494$	1,914.1	1,748.4			
23	26,860	2,858.6	2,474.1	$76,\!449$	$2,\!541.4$	2,719.1			
Total	209,350	2,226.0	2,474.5	209,350	2,046.9	2,276.2			

Table A1. Distribution of workers according to the number of times wages changed in consecutive months

Notes: The table displays the distribution of workers in the estimating sample across the number of times wages changed in consecutive months from January 2015 to December 2016. Under Mean and Std. Dev. we present the mean and standard deviation of wages by each subgroup of workers according to the number of changes. Data source: RAIS 2015-2016.

	(1)	(2)	(3)
	Baseline	No Mobility	No Firm and Worker FEs
<12°C	-0.00025	-0.00025	0.00025
	(0.00045)	(0.00044)	(0.00047)
12-15°C	-0.00023	-0.00011	0.00017
	(0.00014)	(0.00014)	(0.00032)
15-18°C	-0.00029	-0.00029*	-0.00021
	(0.00018)	(0.00016)	(0.00021)
$21-24^{\circ}\mathrm{C}$	-0.00078***	-0.00078***	-0.00097***
	(0.00012)	(0.00012)	(0.00016)
24-27°C	-0.00096***	-0.00098***	-0.00110***
	(0.00011)	(0.00010)	(0.00017)
27-30°C	-0.00141***	-0.00146***	-0.00158***
	(0.00023)	(0.00022)	(0.00033)
$> 30^{\circ} C$	-0.00197***	-0.00201***	-0.00267***
	(0.00032)	(0.00035)	(0.00046)
Obs.	3,468,613	$3,\!114,\!468$	3,468,613
Workers	$209,\!350$	189,303	$209,\!350$
Mean of dep. var.	13.38	13.27	13.38

**Table A2.** Impact of temperature on log of real hourly wages - baseline, no mobility,and no firm and worker FEs

*Notes:* We run additional results conditioning the sample on the workers that did not change municipality, sector, or firm during the time period we analyze (Column 2). Temperature bins range from below  $12^{\circ}$ C to above  $30^{\circ}$ C in sets of  $3^{\circ}$ 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 for Columns (1) and (2). Column (3) results exclude firm and worker fixed effects. 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<0.10, \*\*\* p<0.01.

## Appendix B. Data

#### Details on the handling of employer-employee database

Our source of monthly wages data is the Annual Social Information Report (RAIS). RAIS is an administrative database collected by the Ministry of Labor of Brazil. It encompasses 99 **per cent** of the formal labor force in the country and is, therefore, the most reliable source of labor market data. Monthly wage data are available starting in 2015 and firms are required to inform data for all employees. We employ monthly data starting in January 2015 and ending in December 2016. The RAIS is a large database—its size is approximately 45 GB for each available year. This imposes challenges when treating the database for analysis because of the trade-offs between sample size and computing time.

Within this context, we randomly selected 329,784 workers—approximately 1 per ccent of the sample. We restricted the sample to those aged 25 to 55 and excluded interns, part-time students and workers near retirement, and also agriculture, public administration and military employees (most of the latter have tenure and wages adjustments are much less driven by economic conditions). We lose additional singleton groups — groups with only one observation — because our models include several levels of fixed effects.<sup>1</sup> At the end of the process, we are left with 3,468,613 worker-month observations covering 209,350 total workers. We have run robustness checks using a sample more than three times larger than the estimating sample and results do not change.<sup>2</sup>

#### Dealing with imputation errors in salary figures

The 2016 RAIS database presents imputation errors in the wage variable that we were able to detect and resolve. More specifically, wage data ending in .00 were being divided by 100. For example, a R\$ 1,000.00 monthly salary was reported as R\$ 10.00. The annual average salary figures were reported correctly, so we looped the database looking for and correcting inconsistencies in the monthly salary data. In the end, the twelve-month average we calculate based on monthly salary data matched the annual average wages reported.

<sup>&</sup>lt;sup>1</sup>See this link for more information on singleton observations.

<sup>&</sup>lt;sup>2</sup>Results are available upon request.

We present below two actual data points **before** and **after** the correction. To clarify, the first column refers to the annual average salary that employers reported for each worker in the RAIS database:

• Before the correction

annual average	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
900.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00	9.00
1018.18	9.68	10.08	1778.40	559.87	9.88	9.88	9.88	9.88	9.88	9.88	9.88	9.88

• After the correction

annual average	Jan	Feb	Mar	Apr	May	Jun	Jul	Aug	Sep	Oct	Nov	Dec
900.00	900.00	900.00	900.00	900.00	900.00	900.00	900.00	900.00	900.00	900.00	900.00	900.00
1018.18	968.00	1008.00	1778.40	559.87	988.00	988.00	988.00	988.00	988.00	988.00	988.00	988.00

We see that before the correction, there is a worker with a reported average annual wage of R\$ 900.00; but his/her monthly salary is only R\$ 9.00. Clearly, this was an imputation error which, after corrected, yielded an annual average salary calculated from monthly data equivalent to the annual average salary reported in the first column. The case for the other worker is more interesting. In March and April, monthly salaries are displayed correctly (R\$ 1778.40 and R\$ 559.87, respectively). For the other months, where salary figures ended in ".00", the figures were divided by 100. We corrected them (multiplying by 100), so that the annual average salary calculated from monthly data matched the annual average salary reported in the first column (R\$ 1018.18 in this case).

## References

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.