Labor-market adjustment under extreme heat shocks: Evidence from Brazil *

Victoria Wenxin Xie†

Latest Version

Abstract

How do extreme heat shocks affect immediate hiring, layoff, and job reallocation over the medium run for manufacturing workers? Despite rich evidence on the contemporaneous labor-productivity impact of heat shocks, little is known about what happens to employment over time. In a large-developing-country context, this paper provides worker-level evidence on different labor-market adjustment margins with respect to extreme heat shocks and the underlying transmission mechanism. First, exploiting rich employer-employee matched data (RAIS), I find that quarterly heat shocks lead to significant increases in the propensity of manufacturing-worker layoff. To separately identify the importance of the direct labor-productivity channel among many potential transmission mechanisms, I combine detailed municipality-level agricultural census and crop calendars to isolate heat shocks during the local nongrowing seasons. One extra day with daily mean temperature beyond 31°C during the nongrowing seasons increases the probability of layoff by 0.8 percentage points, equivalent to a 11% increase in the baseline layoff propensity. Second, consistent with the direct labor productivity channel, the impact of heat shocks is stronger for workers engaging in more routine manual-intensive tasks. Third, tracking individuals across job spells, I provide evidence on worker job reallocation. There is limited intersectoral and interregional reallocation for manufacturing workers. A significant proportion of manufacturing workers who experienced heat-related layoffs fail to find any formal employment within 36 months. These results show that heat shocks lead to persistent negative employment effect in the formal manufacturing labor market due to failure in job transitions over the medium run. Transmission-mechanism insights also point to efficient labor-force adaptation strategies and inform a more comprehensive cost assessment of climate-change damages.

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†Correspondence: Department of Economics, University of California at San Diego. Email: w6xie@ucsd.edu

1 Introduction

Many developing countries located in tropical and subtropical zones are vulnerable to climate change due to limited adaptation capacity and high baseline temperatures. Climate change is associated with an expected increase in the frequency of extreme heat days. These drastic environmental shocks could potentially bring about significant changes for the workforce in developing economies. Despite rich micro-level evidence on the contemporaneous labor-productivity impact of extreme heat (Adhvaryu et al., 2016; Hancock et al., 2007), little work has been done to examine the worker-level employment implications of temperature shocks over time. Answers to these questions provide a missing perspective on how climate change affects worker welfare. Assessing the costs of climate change within developing country institutions is also crucial for calibrating country-specific calculation for the social cost of carbon.

In this paper, I provide worker-level evidence on different labor-market adjustment margins with respect to extreme heat shocks and the underlying transmission mechanism. First, using employer–employee-matched data, I find that heat shocks lead to a significant increase in the propensity of immediate manufacturing layoff. I further isolate the direct labor-productivity channel by focusing on heat shocks during the local nongrowing seasons, exploiting rich municipality-level agricultural census and crop calendars. Second, I examine medium-run adjustment margins. Tracking workers across employment spells, I find limited intersectoral and interregional worker reallocation. A significant proportion of manufacturing workers fail to reallocate to another formal-sector job within 36 months. Third, heat shocks during the nongrowing seasons have more pronounced impact on workers in more routine manual-task-intensive occupations.

Heat leads to worker fatigue, lower task performance, and poorer decision making.[1] Given the abundant evidence on the direct labor-productivity impact of heat shocks, one natural question is how much it contributes to economy-wide labor-market adjustment. Contract theory suggests firms cannot fully insure workers against random shocks if efforts are not fully observed (Holstrom and Milgrom, 1987). The magnitude of impact then is an empirical question, depending

[1] Using microdata from assembly lines, Somananthan et al. (2014) and Adhvaryu et al. (2016) show that daily manufacturing labor productivity significantly decreases with temperature. See also Zander et al. (2015), Graff Zivin and Neidell (2014), Niemela et al. (2002), Seppanen et al. (2006), Kjellstrom et al. (2009), and Park (2017).

on the degree of firm-level adaptation and such specific labor-market features as de facto firing costs, downward wage rigidity and interaction with the informal economy. The presence (or absence) of a direct labor-productivity channel also has important implications for climate-change-adaptation policies.[2] To separately identify the direct labor-productivity channel among many potential mechanisms through which weather shocks could affect industrial workers,[3] I exploit unique features of Brazilian employer–employee linked administrative data (RAIS) and rich municipality-level agricultural census. With information on individual workers' month of accession and separation from his/her employer, I am able to match temperature shocks with individual employment outcomes on a quarterly basis to isolate heat shocks during local nongrowing seasons. The underlying assumption is that weather shocks during nongrowing seasons do not operate through agricultural channels (Burgess et al., 2018; Carleton, 2017).

Assessing the labor-market impact of heat shocks from the perspective of worker welfare also requires data on gross instead of net employment flows. Aggregate employment at the firm level provided in industrial surveys only gives net flows and could not inform us of worker displacement if it is accompanied by worker inflow. This issue is particularly important given the multiple, and potentially opposing, channels through which extreme heat could affect the industrial labor market. For example, if temperature increase causes agricultural outmigration into manufacturing due to lower crop yields, we may observe an increase in net firm-level employment. In reality, this increase could be accompanied by agricultural workers substituting existing manufacturing workers, and/or existing workers being laid off due to lower manufacturing labor productivity. Observing worker-level job accession and separation allows me to directly address incumbent worker welfare, whereas the previous literature mostly focused on firm welfare (Colmer, 2017; Santangelo, 2015)

For developing countries, labor-market transitional costs could interact with environmental shocks to further exacerbate the cost of climate change. In particular, if significant cost exists in job transitions, only accounting for the immediate adjustment margins would lead to an underesti-

[2]For example, installing air conditioners in factories versus adopting heat-resistant crops.

[3] Direct labor-productivity channel: Adhvaryu et al. (2016), Somanathan et al. (2014), Heal and Park (2014); interindustry linkages: input–output linkages: Acemoglu et al. (2012), agricultural local-demand channel: Santangelo (2015), Henderson et al. (2017), agricultural labor reallocation: Colmer (2016), agricultural income and nutrition channel: Garg et al. (2017)

mation of total worker welfare losses. To understand medium-run adjustment margins, I exploit the employer–employee linkage feature of RAIS and provide evidence on worker reallocation. Tracking each worker across job spells, I decompose postlayoff transition outcomes into seven collectively exhaustive, mutually exclusive channels by the industry and region of the worker's next job. This helps us better understand the medium-run labor adjustment margins through an examination of worker reallocation between sectors and across municipalities.

First, I find quarterly heat shocks lead to significant manufacturing-labor-market churn. Isolating the direct labor-productivity channel, I show that extreme heat days[4] during nongrowing seasons lead to a higher propensity for manufacturing layoff but has no significant impact on manufacturing hiring. In terms of magnitude, swapping a day with daily mean temperature below 17°C for one with daily mean temperature beyond 31°C during the nongrowing seasons increases the probability of layoff by 0.8 percentage points, equivalent to a 11% increase in the baseline layoff propensity. These results are robust to including a rich set of fixed effects controlling for state- and industry-specific seasonality, state and industry growth trends, time-invariant municipality characteristics, and lagged weather shocks.

Second, in terms of medium-run adjustment margins and worker reallocation, I find limited intersectoral and interregional reallocation for manufacturing workers and a significant failure rate to reallocate. 59% of manufacturing workers find another job in the same industry either locally or in a different municipality. However, 24.3% of all formal manufacturing workers laid off due to heat shocks fail to find any formal sector job within 36 months. This suggests over the medium run, environmental shocks interact with labor-market transitional costs to trigger prolonged unemployment or switching to the informal economy.

Third, consistent with the direct labor-productivity channel, the impact of heat shocks is heterogeneous by occupational task intensity and by gender. Matching worker occupational codes with measures from the Dictionary of Occupational Titles (DOT), I find that manufacturing workers engaging in more routine-manual-intensive tasks are more likely to be laid off during the nongrowing seasons, pointing to a potential source of distributional impact of climate change.

[4] Defined as daily mean temperatures above 31°C.

This paper provides a missing perspective on the aggregate employment implications of extreme temperature shocks associated with climate change and establishes an underlying mechanism using rich microdata. On the aggregate level, temperature shocks have been shown to negatively affect GDP per capita, labor income, economic growth, and exports (Dell et al., 2012; Jones and Olken, 2010; Park, 2017). Manufacturing output changes due to heat shocks are also observed with firm-level evidence from China, India and Indonesia (Colmer, 2017; Deschenes et al., 2018; Somanathan et al., 2014). On the micro-level, evidence from labs, call centers and selected factory assembly lines points to a large negative labor-productivity impact of heat shocks (Adhvaryu et al., 2016; Zander et al., 2015; Graff Zivin and Neidell, 2014; Niemela et al., 2002; Seppanen et al., 2006; Kjellstrom et al., 2009). In contrast, we know surprisingly little about the employment impact of extreme heat shocks, the associated worker displacement and welfare losses, and the importance of the direct labor-productivity channel as a transmission mechanism. Findings in this paper suggest the direct impact of thermal stress on manufacturing workers leads to significantly higher layoff propensity. Identifying the worker-displacement effect is uniquely achieved by examining administrative individual-level data, uncovering a previously ignored source of worker welfare loss from climate change.

Second, this paper offers broader labor-market implications of environmental shocks through various adjustment margins. In addition to the immediate employment effects, labor-reallocation results suggest high worker adjustment costs to extreme heat shocks during worker–firm rematching. I provide first evidence that heat shocks lead to persist negative employment effect in the formal manufacturing labor market due to failure in job transitions over the medium run. To study worker reallocation, I follow empirical methodology recently used in the trade literature to examine the regional labor-market consequence of tariff reductions (Dix-Carneiro and Kovak, 2017a; Menezes-Filho and Muendler, 2011; Autor et al., 2014). Compared with more permanent shocks from trade liberalization, I show that even less persistent temperature shocks lead to significant failure to reallocate, contributing to prolonged individual-worker welfare losses.

Next, I begin by describing the data and presenting relevant empirical facts. Section 3 presents the baseline empirical specification and net impact. Section 4 introduces my methodology to identify the direct labor-productivity channel and main results on transmission mechanisms. Section 5 focuses on medium-run adjustment margins in job reallocation. Section 6 discusses the heterogeneous impact. Section 7 offers further discussions and robustness checks. Section 8 concludes.

2 Data and Empirical Facts

2.1 Data

Worker-level data comes from the Brazilian administrative records Relação Anual de Informações Sociais (RAIS), covering the years from 1990 to 2000. This employer–employee matched contract-level data includes more than 90% of all formally employed workers in Brazil (Menezes-Filho and Muendler, 2011). The records are created to provide information for the federal wage-supplement program (Abono Salarial) and the employer-contribution program (FGTS).

RAIS provides data on worker-level contracts with the firm–plant registration number and the worker ID. Since workers are identified by a unique ID number, which is fixed over time, I am able to track each worker across employers. The finest geographic unit of identification is a Brazilian municipality, which I use to match the administrative records with gridded weather variables. For each worker, there is information on education, tenure, gender, monthly wage, occupation, and month of accession into and separation from each contract. I also have plant-level information on sector, ownership, and plant size.

To construct the worker sample, I take the list of all worker IDs ever to have appeared in RAIS, draw a 10% random sample, and track the selected worker IDs through the years across multiple job spells. In the case of multiple jobs, only the highest paying, last formal employment of the quarter is kept for each worker (Menezes-Filho and Muendler, 2011). For layoffs, I examine job spells conditional on the worker being employed at the beginning of the quarter. Cases of quitting, transfers, retirement, and death are excluded from the analysis. Since we do not observe the worker during unemployment, hiring is defined at the region–industry level.

One important caveat is that RAIS only covers formal sector employment, defined as working with a signed work card. Informal jobs are a significant portion of the Brazilian labor market. According to the 1991 Demographic Census for workers aged 18–64, 28% of manufacturing and 55% of nontradable sector employment is informal (Dix-Carneiro and Kovak, 2017a). Additionally, 89% of agricultural employment is informal. As a robustness check for results on the agricultural sector, I restrict analysis to sugarcane workers only, where workers are predominantly formal and unionized. Comparing with the household survey PNAD, Davis (2017) documents that roughly 60% of sugarcane employment is captured in RAIS. Layoffs are defined in this paper as layoff from the formal sector, which means the worker can be either unemployed or employed informally. Formal sector layoff is meaningful for individual welfare because workers need the signed work card to claim employment-related benefits and labor protections.

Data on weather outcomes are from the ERA-Interim reanalysis archive. I obtain measures of daily mean temperature, dew point temperature, and cumulative rainfall on a $0.125° \times 0.125°$ grid. Relative humidity is calculated from dry bulb and dew point temperature based on Lawrence (2005). Weather variables are then linked to each municipality using GIS data from the Global Administrative Borders.

Regional crop production data are from the Municipal Agricultural Production Survey (PAM), maintained through the data portal (SIDRA) by the Brazilian Institute of Geography and Statistics (IBGE). This survey provides the annual production value, area, and average yield of all temporary and permanent crops in Brazil by municipality. I use the municipality crop specific production value from the PAM to determine the main crop of each municipality. To identify the nongrowing seasons of each municipality, I use the Brazilian crop calendars collected by the USDA World Agricultural Outlook Board. These calendars provide regional crop-growing cycles in Brazil by sowing, growing, and harvest stages and allow me to distinguish between growing and nongrowing seasons of major crops in Brazil. Finally, for heterogeneity analysis, I use the occupational-task intensity measures from the Dictionary of Occupational Titles constructed by Autor, Levy, and Murnane (2003).[5] An underlying assumption here is that the relative ranking of occupational task intensity is preserved across U.S. and Brazilian occupations.

[5] Concordance from the US Census occupational codes to the ISCO-88, and to the Brazilian occupational codes CBO are from Autor and Dorn (2013), the Center for Longitudinal Studies in UCL, and Muendler et al. (2004).

2.2 Empirical Facts

In this section, I first briefly review the literature on thermal stress and labor productivity. Next, I show the raw distribution of daily average temperature during the sample period of analysis in Brazil. Third, I present the spatial distribution of extreme heat shocks to illustrate from where the temperature variations exploited in later sections come.

One focus of this paper is to identify the direct labor-productivity channel as a transmission mechanism through which heat affects manufacturing employment. To put the extreme heat shocks in Brazil into context, I briefly review key evidence on thermal stress and labor performance. A large body of literature has documented a highly nonlinear relationship between temperature and individual labor productivity. Recent evidence from selected Indian garment factories documents 29.5°C as the physiological threshold above which temperature strongly impedes human functioning (Adhvaryu et al., 2016). Meta-analysis in ergonomics (Pilcher et al., 2002; Hancock et al., 2007) summarizing multiple experimental studies reveals that task performance losses start to occur with the Wetbulb Global Temperature (WBGT) equivalent of 28°C, at 80% relative humidity and normal sea level air pressures. Sharp performance losses are observed with the WBGT equivalent of 32°C. On the aggregate level, Hsiang (2010) estimates that economic production losses begin at 29°C.

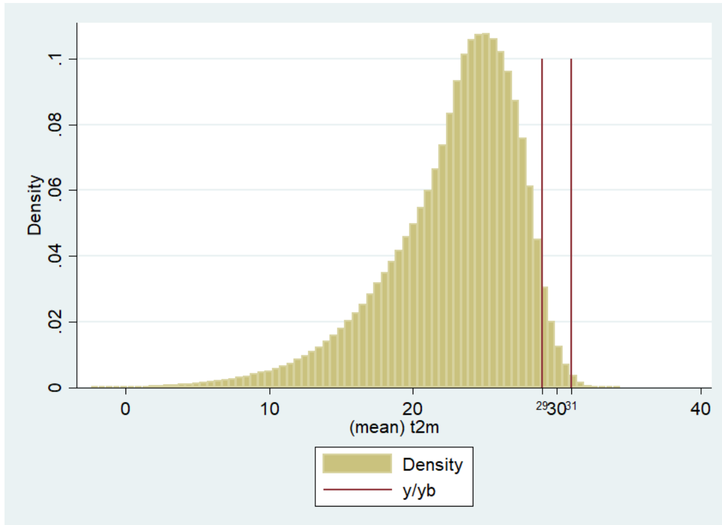
As an important emerging economy, Brazil spans several climate zones and provides rich regional temperature variations. Figure 1 plots the probability density distribution of daily average temperature of all municipalities in Brazil, from 1990 to 2000. The mean is 22.82°C, with 3.43% of the observations above 29°C, and 0.24% of observations above 31°C. Throughout this paper, I define an *extreme-heat day* as having daily mean temperature above 31°C. With climate change, this graph is expected to develop a fatter right tail. Because of the nonlinear relationship between labor productivity and temperature, one expects to observe a strong impact of days in the extreme-heat category.

Figure 2 plots the spatial distribution of daily mean temperature, averaged over the period from 1990 to 2000. Figure 3 illustrates the spatial distribution of extreme-heat days. For each municipality, I aggregate the number of days with daily mean temperature above 31°C from 1990 to 2000. The white regions did not experience an extreme-heat day during the sample period, such as the Amazons. The colored municipalities had from 1 to 471 days of extreme heat. The municipality in the 95th percentile experienced 46 days of extreme heat cumulatively during the sample period. Since extreme-heat shocks display spatial clustering, I include municipality fixed effects in all subsequent analysis to control for any region-specific time-invariant characteristics that correlate with temperature.

Although extreme heat days are rare in Brazil during the period of my analysis (1990–2000), climate projections indicate these days will drastically increase based on our current emission trajectory (Sanford et al., 2014). Figure 4 plots the projected change (compared to the baseline period 1986–2005) in annual extreme-heat days, defined as daily mean heat index above 35°C, equivalent to daily mean temperature above 31°C with relative humidity at 60%. Predictions are made assuming the Representative Concentration Pathway 8.5 scenario, which we would surpass without sharp downward transitions. The underlying data comes from the Coupled Model Intercomparison Project (CMIP5) used in the Intergovernmental Panel on Climate Change (IPCC) fifth assessment report, and the World Bank Group's Climate Knowledge Portal.

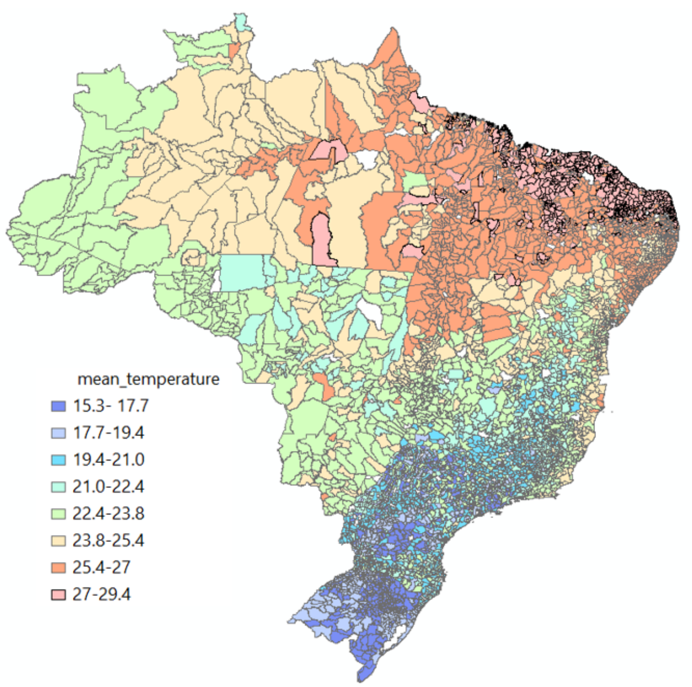
Figure 4 shows large regional disparity in predicted increase of extreme-heat days. For the period 2040–2059, the predicted change in annual extreme-heat days is 0.95 for a southern municipality like Sao Paulo, 69.75 days for a central municipality such as Palmas, and 34.5 days for a northeastern municipality such as Teresina. Later in my analysis, I discuss how these differences in predicted heat exposure could lead to large variations in regional manufacturing employment outcomes.

Figure 1: Distribution of daily average temperature



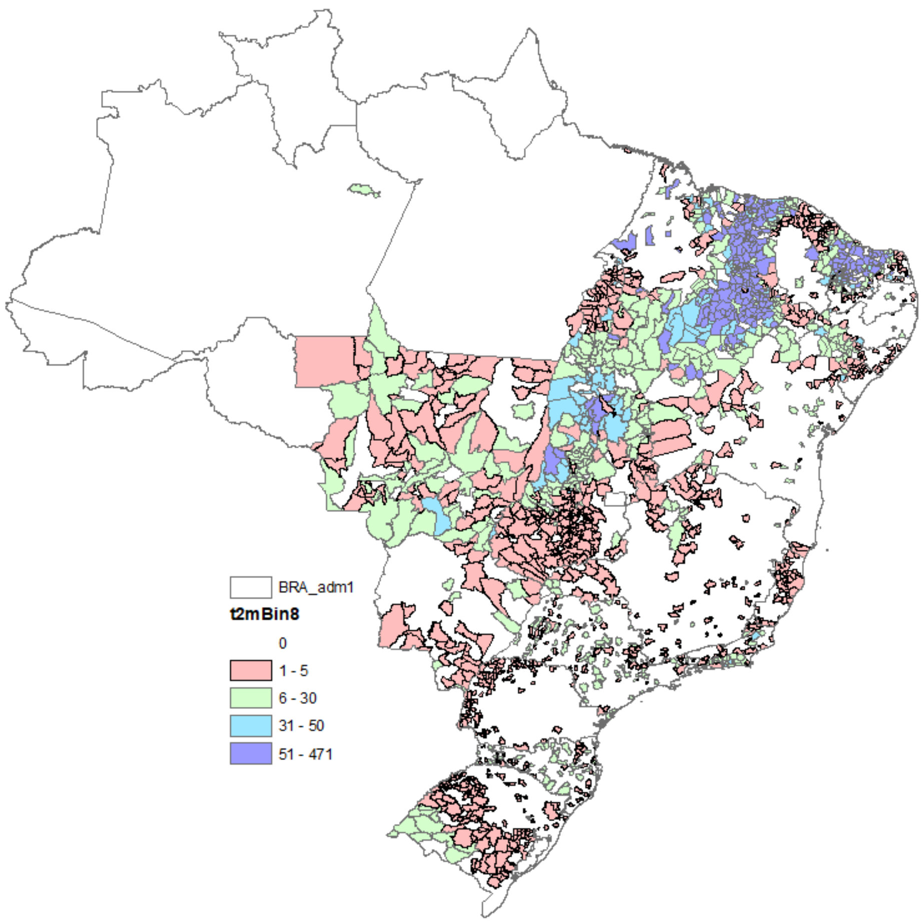
This figure plots the probability density distribution of daily mean temperature for all municipalities in Brazil, from 1990 to 2000. Daily mean temperature (t2m) on the X-axis is measured in terms of degrees Celsius. The two red vertical lines represent the 29°C and 31°C thresholds.

Figure 2: Spatial distribution of daily mean temperature from 1990 to 2000



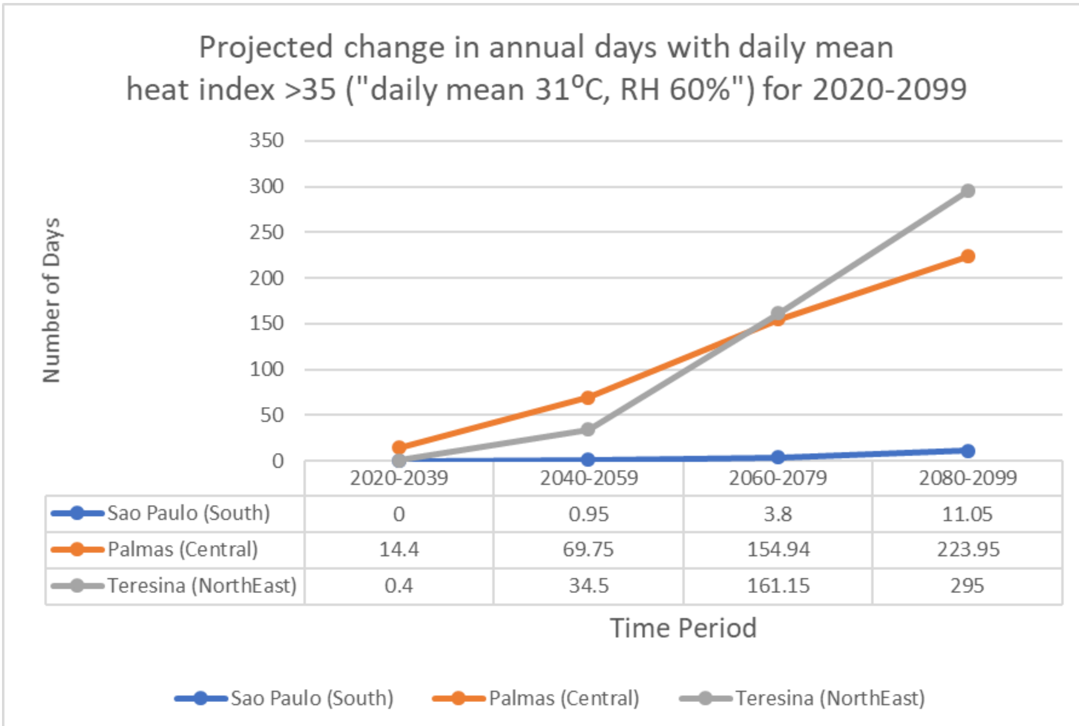
This map plots the spatial distribution of daily mean temperature, averaged over the period from 1990 to 2000. The finest geographic unit is a Brazilian municipality. Ranges in the legend are in terms of degrees Celsius.

Figure 3: Spatial distribution of extreme heat shocks (daily mean temp > 31°C)



This map illustrates the spatial distribution of cumulative extreme-heat days. For each municipality, "t2mBin8" represents the total number of days with daily mean temperature above 31°C from 1990 to 2000. The finest geographic unit is a Brazilian municipality.

Figure 4: Prediction of future extreme heat days: CMIP5, RCP8.5, access1_0



This chart shows the predicted change in annual count of extreme-heat days, defined as daily mean heat index above 35°C, relative to the reference period (1986–2005). These days represent extremely uncomfortable conditions and are equivalent to daily mean temperature of 31°C, at relative humidity 60%. The point estimates are given for three randomly selected cities: Sao Paulo, Palmas. and Teresina, located in the south, central, and northeast regions in Brazil. Projections are given by the Coupled Model Intercomparison Project (CMIP5) under the "access1_0" model, assuming the Representative Concentration Pathway 8.5 (RCP 8.5) scenario. These data are available through the World Bank Group's Climate Knowledge Portal, and covers periods 2020–2039, 2040–2059, 2060–2079, and 2080–2099.

3 Baseline: Immediate Impact

Do quarterly temperature shocks lead to changes in the propensity of manufacturing worker layoff and hiring? Existing literature provides ample evidence on the labor-productivity impact of heat shocks. Whether these productivity shocks cause changes in employment outcomes, however, is largely unexplored. A rather complex array of institutional, firm- and worker-specific factors matter for the employment implications of heat-related productivity shocks. These include, but are not limited to, the labor-market institutions on hiring and firing costs, the presence of nominal wage rigidity, the degree of firm-level adaptation, heterogeneity in workers' sensitivity to heat, and firm managers' attitudes towards ambiguity of quality signals (Ilut et al., 2018). Section 7 of this paper provides suggestive evidence on how some of these factors matter in the Brazilian context.

Other than the direct labor-productivity channel, there are multiple potential mechanisms through which heat shocks could affect the manufacturing labor market. Given what we know about temperature and crop yields (Lobell et al., 2011), heat shocks could influence manufacturing through various interindustry linkages with agriculture, including agricultural outmigration, changes in farmer income and local demand, and changes in raw material prices. Section 4 discusses this issue in greater detail and addresses the identification challenge of transmission channels by isolating heat shocks during the local nongrowing seasons. Before diving into the mechanisms, I start with a baseline empirical specification and examine the net impact of heat shocks through all combined channels.

3.1 Empirical Strategy

The baseline empirical framework is a fixed-effect model

$$\begin{aligned} Y_{ijmt} = \sum \beta_k Tempbin^k_{m,t} + f(Rain_{m,t}, Humidity_{m,t}) + \alpha_1 X_{it} \\ + \theta_{qy} + \theta_{yr} + \theta_{qr} + \Phi_{yj} + \Phi_{qj} + \Phi_{rj} + \tau_m + \epsilon_{ijmt}, \quad (1) \end{aligned}$$

where Y_{ijmt} is the binary outcome of worker layoff, for worker i, employed in industry j, residing in municipality m, at time t. Allowing for nonlinear effects, $Tempbin^k_{m,t}$ is the number of days in a quarter with daily mean temperature within the specified range k.[6] $f(Rain_{m,t}, Humidity_{m,t})$ controls for the cumulative rainfall and relative humidity. X_{it} is a vector of worker and plant-level controls including worker education, occupation categories, tenure, potential labor-force experience, plant size, and plant skill composition.

To causally identify the effect of heat shocks on worker layoff, a rich set of fixed effects are included to control for confounders that could be correlated with temperature and to rule out spurious relationships. First, since we are examining individual layoff decisions at the quarterly frequency, it is crucial to include controls for seasonality which may correlate within-year employ-

[6] Tempbin1, where $t < 17°$C, is omitted.

ment cycles with temperature fluctuations. To control for state-specific employment seasonality, I include Quarter × State fixed effects, and, for industry-specific seasonality, I include Industry × Quarter fixed effects.

One may also imagine that a general warming trend in temperature might be correlated with national business cycles during this period. I address this concern by including Quarter × Year fixed effects. Further, warmer regions may have different institutions or other geographic features that lead to different employment patterns. To control for any time-invariant municipal characteristics, I include Municipality fixed effects. Finally, I include State × Year and Industry × Year fixed effects to control for state and industry growth trends, and State × Industry fixed effects for regional industrial patterns. This also means the temperature variations I exploit are deviations from averages, instead of variations in raw temperature. Standard errors are clustered at the mesoregion level to allow for serial and spatial correlation.

3.2 Results

We first examine the baseline immediate impact of heat shocks on individual layoff and hiring, separately for manufacturing and agricultural workers. These results show that, after pooling together all seasons and several potential mechanisms, temperature shocks significantly influence individual labor-market outcomes.

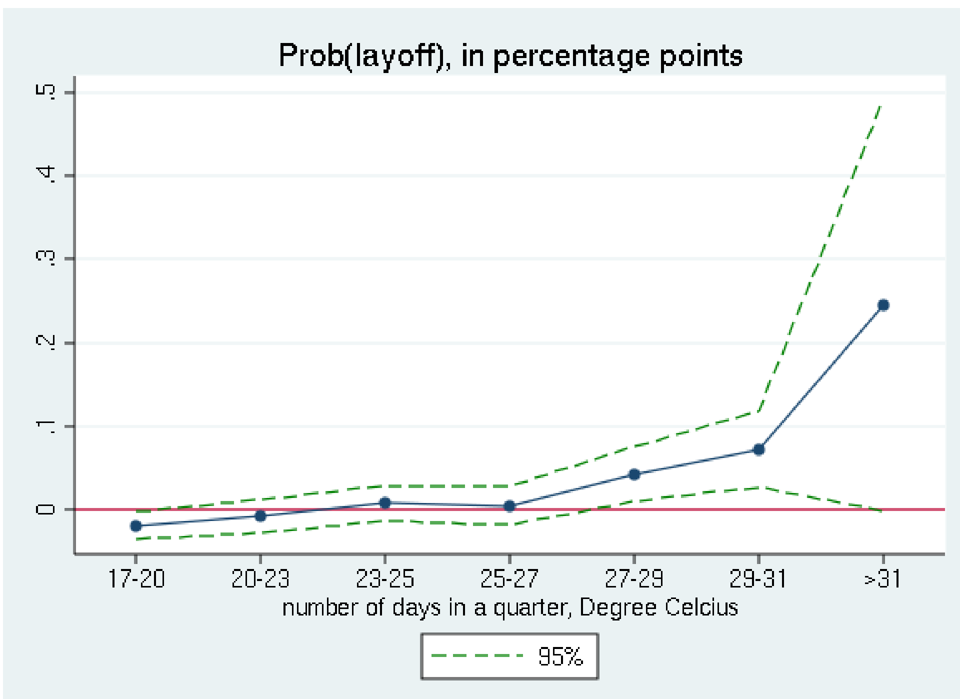
We start with individual outcomes on layoff. Figure 5 illustrates that the probability of manufacturing-worker layoff increases in a nonlinear manner as temperature increases.[7] Specifically, this figure plots the regression coefficients associated with each daily mean temperature bin, where the <17°C bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity for worker layoff, relative to the impact of a day with daily mean temperature less than 17°C. We start to see a significant effect with an additional day where daily mean temperature goes beyond 27°C. The point estimate indicates that swapping a day with daily mean temperature below 17°C for one with daily mean temperature beyond 31°C increases the probability of layoff

[7] Coefficients are multiplied by 100.

by 0.236 percentage point, or a 3% increase in the baseline propensity (7.867 percentage points). Similarly for agricultural workers, in Figure 6, we see that all estimates associated with daily mean temperature beyond 27°C are positively significant at the 5% level.

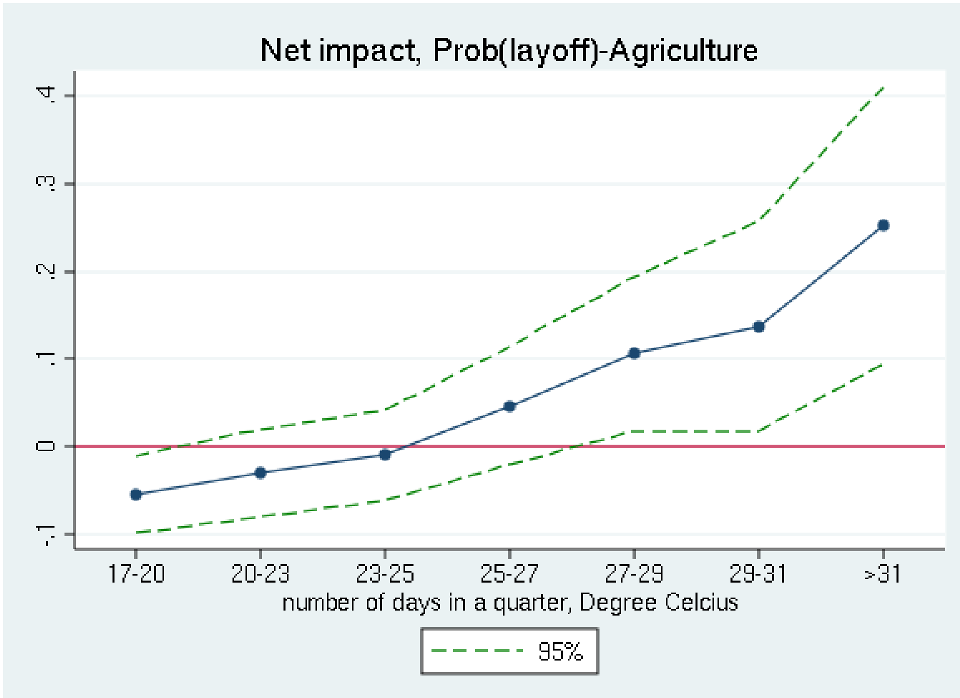
Next, we look at changes in baseline hiring rates. Since we do not observe the worker if he or she is unemployed, I construct region–industry hiring shares by aggregating the total number of individual accessions in each quarter at the municipality–industry level, normalized by each municipality's population in 1999. The empirical framework follows Equation 1, except that we do not include worker- or plant-level controls. Figure 7 shows that heat shocks lead to a lower propensity for hiring agricultural workers but has no significant impact on manufacturing hiring.

Figure 5: Quarterly heat shocks and manufacturing layoff: Net impact



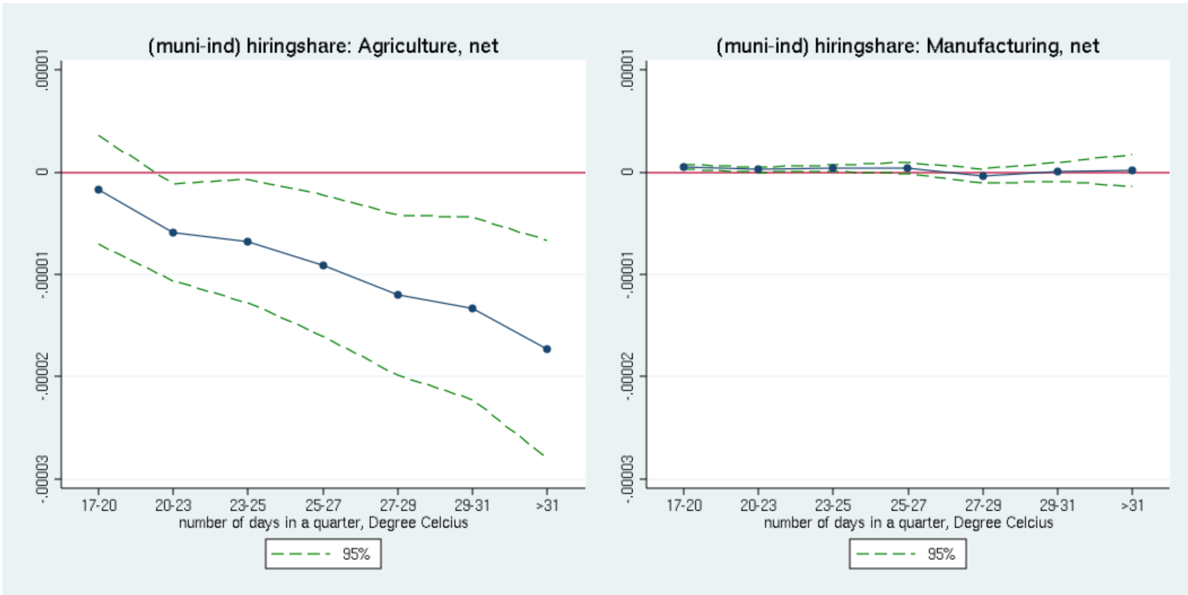
Manufacturing Labor Market—Each point estimate reflects an individual regression coefficient, β_k, following Equation 1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity for worker layoff, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry and municipality fixed effects, along with other weather covariates and a rich set of firm- and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

Figure 6: Quarterly heat shocks and agricultural layoff: Net impact



Agricultural Labor Market—Each point estimate reflects an individual regression coefficient, β_k, following Equation 1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity for worker layoff, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry and municipality fixed effects, along with other weather covariates and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

Figure 7: Agricultural vs. manufacturing hiring: Net impact



Agricultural and Manufacturing Labor Market—Each point estimate reflects an individual regression coefficient, β_k, following Equation 1. The dependent variable is region–industry hiring share, constructed by aggregating the total number of individual accessions in each quarter at the municipality–industry level, normalized by each municipality's population in 1999. The independent variables are the numbers of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the hiring share, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry, municipality fixed effects, along with other weather covariates (see text for details). Standard errors are clustered at the mesoregion level.

4 Transmission Mechanism

In Section 3, I show that quarterly heat shocks lead to immediate manufacturing and agricultural labor-market churn. These meaningful changes in employment outcomes could be driven by a wide range of underlying mechanisms, possibly operating in opposing directions. We need to rely on additional research design to identify the presence of any specific mechanisms.

Motivated by recent evidence on thermal stress and labor productivity (Adhvaryu et al., 2016), I now focus on identifying the importance of the direct labor-productivity channel in driving heat-related manufacturing layoff and hiring. I first introduce a methodology to isolate the direct labor-productivity channel from other transmission mechanisms, using the Brazilian agricultural surveys and regional crop calendars. Next, I present main results on manufacturing-worker layoff and hiring during growing versus nongrowing seasons. In Appendix C, to verify the underlying identifying assumption, I look at the formal agricultural labor market during growing versus nongrowing seasons.

4.1 Identifying the Physiological Channel

Recent evidence from both the climate–economy and ergonomics literature points to a significant labor-productivity drop as temperature increases.[8] However, we know little about whether this direct labor-productivity impact leads to changes in worker employment outcomes in an economy-wide setting. Establishing this crucial link helps us understand how firms and workers share the cost of climate change, and how to better design social-welfare programs in the presence of such environmental shocks.

Numerous factors are relevant when we assess how heat-related productivity shocks matter for market outcomes such as employment. For example, if individuals are heterogeneous in their sensitivity to heat, firms may lay off workers who experience the most productivity drop during heat shocks, or those who are less likely to exert effort when exposed to heat. Transitory heat shocks may also lead to layoff in the presence of downward nominal wage rigidity. The individual employment impact of heat shocks also depends on the degree of firm adaptation either through installing air conditioners or adaptive managerial practices.[9] Overall, the employment implications of the direct labor productivity channel is a rather complex empirical question rooted in labor-market institutions and firm- and worker-specific factors.

Identifying the transmission mechanism through which heat affects the manufacturing labor market also has crucial policy implications for targeting efficient climate-change adaptation strategies. If the direct labor-productivity channel is important in contributing to the labor-market impact of extreme heat shocks, we may think about installing more air conditioners in factories to mitigate the negative labor-productivity effect. On the other hand, if manufacturing workers are laid off due to indirect agricultural channels, the policy implications would be quite different.

[8] Evidence from assembly lines, laboratories, meta-analysis, and self-reported surveys: Somananthan et al. (2014), Adhvaryu et al. (2016), Zander et al. (2015), Graff Zivin and Neidell (2014), Niemela et al. (2002), Seppanen et el. (2006), Kjellstrom et al. (2009), Park (2017)

[9] Adhvaryu, Kala and Nyshadham (2014) show that good managers adapt to air pollution shocks through worker task reassignment.

For example, if heat shocks reduce crop yield and raise agricultural input prices, input tariff liberalization may be an effective response. Similarly, establishing farmer-income stabilization programs would be helpful if the local demand channel is present.

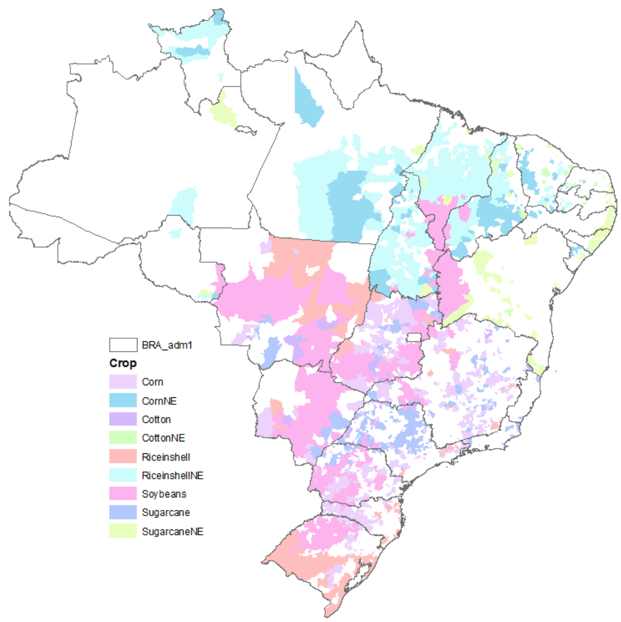
The strategy I adopt in this paper to investigate the importance of the direct labor-productivity channel is by isolating heat shocks during the nongrowing seasons of each municipality. The underlying assumption is that heat shocks during local nongrowing seasons do not influence agricultural outcomes, allowing me to shut off various indirect agricultural channels through which temperature shocks affect the manufacturing labor market. A similar methodology has been recently adopted (Carleton, 2017; Burgess et al., 2018) to study the mechanism of how heat affects mortality. In Appendix C, I verify this identifying assumption by comparing outcomes during growing versus nongrowing seasons in the agricultural labor market.

Discerning the regional nongrowing seasons in Brazil involves two steps. Exploiting the Municipal Agricultural Production Surveys (PAM), I first determine the main crop of each municipality based on crop-production shares. Figure 8 shows the main crop of each municipality in Brazil ranked by production values. Major seasonal crops in Brazil include corn, cotton, rice, soybean, and sugarcane. The white areas represent municipalities whose main crop has year-round growing seasons. Next, I use the Brazil crop calendars from the USDA World Agricultural Outlook Board to determine the nongrowing seasons of each crop.[10] A quarter for a municipality is categorized as the nongrowing season if it is the regional nongrowing season of the main crop of that municipality.

Figure 9 presents the resulting map showing the nongrowing seasons of each municipality. Excluding the municipalities with year-round growing seasons, quarter three, from July to September, is the main nongrowing season for most central and southern regions in Brazil. In the northeast, nongrowing seasons arrive later in quarter four, from October to December. This categorization corresponds approximately to three months before the arrival of the rain season, which is the approach adopted in Burgess et al. (2018) and Garg et al. (2017) to identify Indian nongrowing seasons.

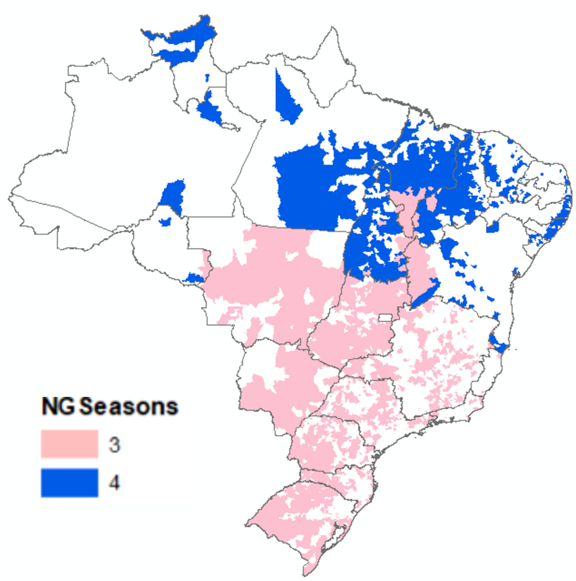
[10] These nongrowing seasons also correspond to those in the crop calendars by Sacks et al. (2010), which result from digitizing and georeferencing existing observations of crop planting and harvesting dates.

Figure 8: Main crop of municipality by production value



This map represents the main crop of each municipality in Brazil ranked by crop production values (see text for details). Major seasonal crops in Brazil include corn, cotton, rice, soybean, and sugarcane. The white areas represent municipalities whose main crop has year-round growing seasons (see text for details).

Figure 9: Main-crop nongrowing season by production value



This map shows the nongrowing seasons in Brazil. A quarter for a municipality is categorized as the nongrowing season if it is the regional nongrowing season of the main crop of that municipality.

4.2 Manufacturing Layoff and Hiring: Nongrowing vs. Growing Seasons

Having identified the regional nongrowing seasons, we are now ready to examine how important the direct labor-productivity channel is for manufacturing layoff. Intuitively, heat shocks during the nongrowing seasons do not affect agricultural outcomes, therefore allowing me to shut off multiple indirect agricultural channels and identify the direct labor-productivity channel. We proceed by comparing regression results during the growing versus nongrowing seasons, and then testing sensitivity in a series of alternative specifications.

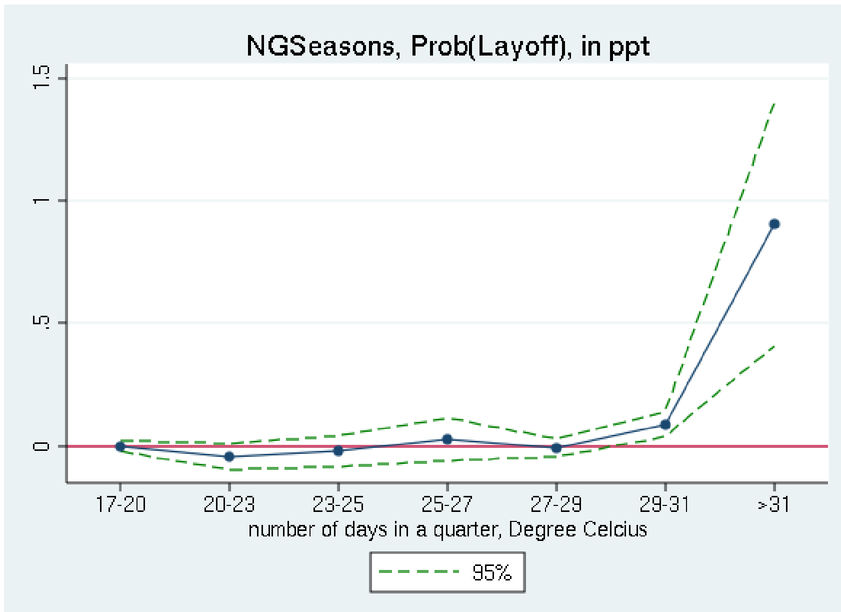
4.2.1 Nongrowing Seasons

We first estimate the effect of heat shocks on manufacturing worker layoff in the nongrowing seasons. Under the assumption that nongrowing-season shocks have no effect on agricultural outcomes, I isolate the impact of the direct labor-productivity channel by focusing on nongrowing season shocks. The empirical framework follows Equation 2, which is a modification of Equation 1, where the dummy for growing seasons, $D^{GS}_{m,q}$, is interacted with temperature bins and other weather covariates.

$$\begin{aligned} Y_{ijmt} = \sum \beta_k Tempbin^k_{m,t} + \sum \beta_s D^{GS}_{m,q} * TempBin^s_{m,t} + \beta_1 D^{GS}_{m,q} + f(Rain_{m,t}, Humidity_{m,t}) \\ + D^{GS}_{m,q} * f(Rain_{m,t}, Humidity_{m,t}) + \alpha_1 X_{it} + \theta_{qy} + \theta_{yr} + \theta_{qr} + \Phi_{yj} + \Phi_{qj} + \Phi_{rj} + \tau_m + \epsilon_{ijmt} \end{aligned} \tag{2}$$

Figure 10 shows how the propensity for manufacturing-worker layoff varies with temperature during nongrowing seasons. We see a significant, highly nonlinear relationship, with extreme-heat days having a pronounced impact, starting with daily mean temperature above 29°C. In particular, the point estimate indicates that replacing a day with daily mean temperature below 17°C with one with daily mean temperature beyond 31°C increases the probability of layoff by 0.8 percentage points, a 11% increase from the baseline layoff propensity (7.2 percentage points). This highly nonlinear relationship is consistent with the thermal-stress literature on heat and individual labor productivity. Meta-analysis in ergonomics (Hancock et al., 2007) documents that task performance losses start to occur at 28°C and 80% relative humidity. Sharp performance losses occur at 32°C. Evidence from Indian garment factories documents 29.5°C as the physiological threshold above which temperature strongly impedes of human functioning (Adhvaryu et al., 2016).

Figure 10: Manufacturing worker layoff: nongrowing seasons, with interacting specification



Manufacturing Labor Market, Nongrowing Seasons, Interaction Specification - Each point estimate reflects an individual regression coefficient, β_k, where the dependent variable is the binary outcome on worker layoff. Following Equation 2, we estimate the specification where $D^{GS}_{m,q}$ is a dummy for growing seasons. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C, *in the nongrowing seasons*. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

The nongrowing season results in Figure 10 show that through the direct labor-productivity channel, thermal stress starts to significantly affect manufacturing layoff decisions only when daily average temperature goes beyond 29°C. This is consistent with the existence of firing and hiring costs in the formal sectors. Intuitively, moderate productivity losses do not justify firing costs, but large productivity losses under extreme heat increase the probability of worker layoff.

Taking the point estimate for the extreme-heat temperature bin (daily mean >31°C), we could compare the difference in layoff propensity for manufacturing workers in different regions. Since my identifying variations in the fixed-effects framework come from quarterly average temperature deviation, I first regress the raw number of days in the extreme-heat temperature bin on the fixed effects in Equation 1. Then I examine the distribution of the residuals. A municipality in a quarter with a "residual heat shock" in the 99th percentile experiences, on average, three extreme-heat days relative to the fixed-effect averages. Compared with a municipality that does not experience any extreme-heat days relative to the averages, the difference in the propensity of manufacturing worker layoff is 2.4 percentage points, equivalent to 33.3% of the average baseline layoff propensity (7.2 percentage points). This number should be interpreted with caution. Since the temperature bin setup assumes equal effect of each additional extreme heat day, my point estimate does not take into account possible harvesting effects.

Given these point estimates, future climate predictions also imply large disparities across regional local labor markets in Brazil. Recall from Figure 4 that during 2040–2059, under the RCP8.5 scenario, the central city of Palmas is projected to have 69.75 more days annually, or 17.4 more days quarterly of extreme heat. In contrast, the southern city of Sao Paulo incurs only 0.2 more extreme-heat days per quarter. These striking variations in the predicted number of extreme-heat days indicate large labor productivity gap across regions, and likely large second-moment differences in the frequency of productivity shocks from extreme heat. While this paper focuses only on increases in the second moment, absent adaptive capital and perfect labor mobility, both changes have important implications for disparity in regional employment outcomes.

These results on the direct labor-productivity channel are robust to a number of alternative specifications. First, to rule out worker sorting according to heat shocks based on unobserved time-invariant ability, I test sensitivity to including worker fixed effects. Second, lagged response to heat shocks during the growing seasons could influence layoff decisions during the nongrowing seasons if temperature shocks are serially correlated, so I control for lagged weather shocks. Third, to ensure the results are not driven by a few influential outliers, I run a robustness check implementing Cook's distance regression diagnostics. The main results hold under all these alternative specifications (Appendix A, Figures A.1, A.2).

Why might quarterly heat shocks lead to manufacturing layoff? In a simple setting, heat shocks during the nongrowing seasons lower marginal labor productivity. Incentive providing firms could adjust by either lowering wages or laying off workers, particularly those with low labor force attachment.[11] This is especially plausible given that the Brazilian labor market during this period is characterized by high turnover rate. Messina and Sanz-De-Galdeano (2014) show that wages in Brazil during the 1990s were subject to substantial downward rigidity due to indexation policies, and that wage adjustment was largely achieved through labor market turnover.

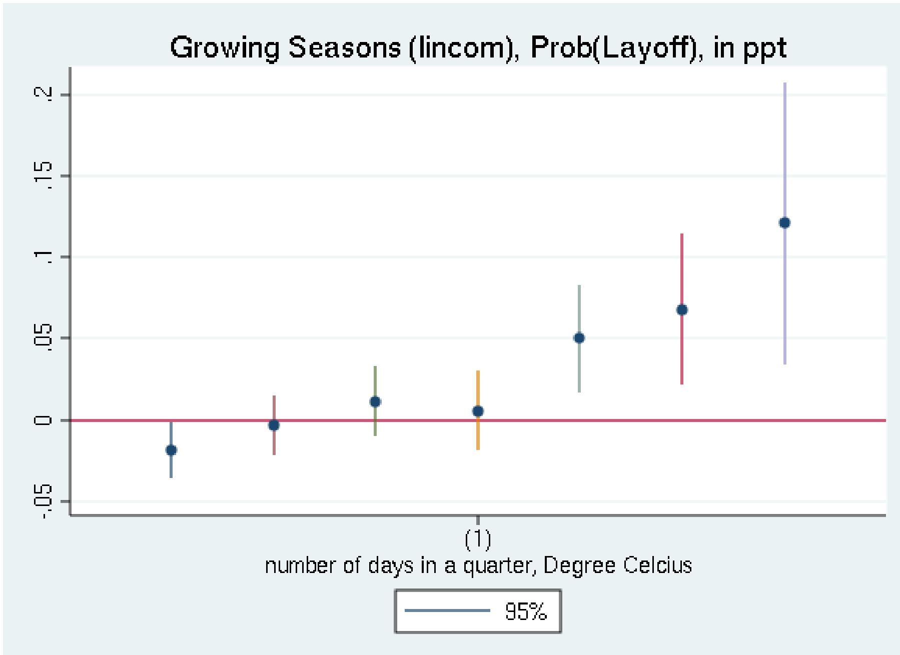
Many other relevant factors could also be at play. For example, the workers laid off could be of lower quality. Recent papers show that workers are heterogeneous in their sensitivity to heat or willingness to exert effort under adverse work conditions (Graff Zivin and Neidell, 2014). Learning a worker's type could be informative of how she/he responds to other types of shocks to workplace conditions. This worker-specific information could be unknown to the employer ex-ante, but revealed after extreme heat days, leading to layoff of those who experience a larger productivity drop. Firms may also face cash flow constraints (Chodorow-Reich, 2013). Yet another possibility is that workers are transitioning into the informal sector. In Section 7, I offer further evidence with respect to some of these factors.

4.2.2 Growing Seasons

Unlike the nongrowing season impact, which is only driven by the direct labor-productivity channel, heat shocks during growing seasons could influence manufacturing hiring and layoff via a complex array of transmission mechanisms, both directly and through interindustry linkages. As we see in Figure 11, manufacturing layoff propensity during growing seasons also increases with temperature, but the magnitude is much smaller at extreme temperature ranges. Replacing a day with daily mean temperature below 17°C with one with daily mean temperature beyond 31°C increases the probability of layoff by 0.12 percentage point, or a 1.5% increase from the baseline layoff propensity (7.9 percentage points).

[11] By law, manufacturing firms in Brazil pay a moderate penalty for firing workers without cause. The cost amounts to about 8%–19% of the expected UI benefits paid to workers (van Doornik et al., 2017). De facto cost of firing may be lower for firms further from enforcement offices (Almeida and Carneiro, 2012).

Figure 11: Quarterly heat shocks and manufacturing layoff: Growing seasons



Manufacturing Labor Market, Growing Seasons, Interaction Specification - Each point estimate reflects an individual regression coefficient, β_k, where the dependent variable is the binary outcome on worker layoff. Following Equation 2, we estimate the specification where $D^{GS}_{m,q}$ is a dummy for growing seasons. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The linear combination of coefficient $\beta_k + \beta_s$ is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C, *in the growing seasons*. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

The point estimates in Figure 11 can be interpreted as the combined impact of the direct labor-productivity channel and indirect agricultural channels through interindustry linkages. Given the fixed-effects framework and controls on state- and industry-specific seasonality, I am not able to directly compare the magnitude of estimates in Figure 10 and Figure 11 and infer the direction of impact through agricultural channels. This is because the identified magnitude through the direct labor-productivity channel could be different in growing versus nongrowing seasons due to different baseline temperatures across seasons.

The existing literature suggests that the indirect agricultural channels could be working in an opposing direction as the direct labor-productivity channel at extreme temperature ranges. Colmer (2017) finds that as temperature increases, the manufacturing sector absorbs displaced agricultural workers during growing seasons. If the incoming workers complement incumbent manufacturing workers, existing workers might benefit from this agricultural outmigration channel. If on the other hand, incoming workers substitute, then incumbent manufacturing workers may experience displacement. In Section 5, I offer direct evidence on intersectoral labor reallocation by directly tracking workers across job spells and decomposing postlayoff channels.

5 Labor Reallocation

In the presence of significant costs in the job reallocation process, only accounting for the immediate adjustment margins would lead to underestimation of total worker welfare losses. The unique employer-employee linkage feature of RAIS allows me to examine individual job reallocation and better understand the medium-run adjustment margins for heat-related layoffs. In this section, I present an empirical strategy and provide evidence on manufacturing worker reallocation between sectors and across municipalities.

5.1 Empirical Strategy

To understand heat-related worker reallocation, I construct dummies for seven mutually exclusive, collectively exhaustive categories for postlayoff transition outcomes. Conditional on layoff, I assign the worker to be in one of the following seven categories according to reallocated sector and region: (1) Move to the manufacturing sector in the same municipality within 36 months, (2) Move to the manufacturing sector in a different municipality within 36 months, (3) Move to the agricultural sector in the same municipality within 36 months, (4) Move to the agricultural sector in a different municipality within 36 months, (5) Move to the service/primary sector in the same municipality within 36 months, (6) Move to the service/primary sector in a different municipality within 36 months, or (7) Fail to move to any formal employer within 36 months.

The data requirement for studying worker reallocation is high. Using RAIS, I am able to track each worker across job spells over time, identifying employers by sector and municipality.[12] The

[12]To study worker reallocation 3 years postlayoff, I do not consider layoffs that occur during the last 3 years of my sample period.

empirical specification follows the fixed-effect model in Equation 3:

$$Y^p_{ijmt} = \sum \beta_k Tempbin^k_{m,t} + f(Rain_{m,t}, Humidity_{m,t}) + \alpha_1 X_{it} + \theta_{qy} + \theta_{yr} + \theta_{qr} + \Phi_{yj} + \Phi_{qj} + \Phi_{rj} + \tau_m + \epsilon_{ijmt} \tag{3}$$

where Y^p_{ijmt} is the binary variable for whether the worker i, employed in industry j, residing in municipality m, at time t, belongs to a particular postlayoff category p.[13] For example, Y^1_{ijmt} takes the value of one if a worker experiences a layoff at time t, and subsequently moves to a manufacturing employer in the same municipality within 36 months, and zero otherwise. Because Y^p_{ijmt}s are conditional on layoff, a worker who has never experienced a layoff during the sample period will have a value of zero for all the postlayoff transition outcomes.

The rest of this fixed-effect specification is the same as in Equation 1. Allowing for nonlinear effects, $Tempbin^k_{m,t}$ is the number of days in a quarter with daily mean temperature in the specified range k.[14] $f(Rain_{m,t}, Humidity_{m,t})$ controls for the cumulative rainfall and relative humidity. X_{it} is a vector of worker and plant-level controls including worker education, occupation categories, tenure, potential labor force experience, plant size, and plant-skill composition.

I include Quarter*Sate, State*Year, and Quarter*Year fixed effects to control for state-specific seasonality in employment, state growth trends, and national business cycles. Industry*Year and Industry*Quarter fixed effects control for industry-growth trends and industry-specific seasonality. State*Industry fixed effects control for regional industrial patterns of specialization. Municipality fixed effects control for any time-invariant municipality characteristics. Standard errors are clustered at the mesoregion-level to allow for spatial and serial correlation.

5.2 Results: Reallocation for Manufacturing Workers

I examine medium-run worker-level adjustment margins of heat shocks by looking at individual job reallocation channels after heat-related layoff. If heat shocks cause contemporaneous layoff

[13] To fully decompose the reallocation channels, we run eight regressions in total.

[14] Tempbin1, where $t < 17°$C, is omitted.

but workers quickly transit to another formal employer in a short period of time, the associated medium-run individual welfare loss could be small. However, as I show, a significant portion of workers who experience layoff due to heat shocks fail to find any formal employer within 36 months, leading to prolonged individual labor-market impact. In this subsection, I focus on decomposing manufacturing reallocation outcomes following heat shocks in all seasons. Appendix B offers further evidence for nongrowing seasons.

As illustrated in Table 1, the impact of heat shocks on postlayoff transition outcomes in columns 1-7 sum to the impact on total layoffs, given in column 2. Swapping a day with daily mean temperature below 17°C for one with daily mean temperature beyond 31°C increases the total probability of manufacturing layoff by 0.25 percentage points. Note this point estimate is slightly different from the magnitude in Figure 5 because I do not look at layoffs during the last 3 years to analyze reallocation over the 3-year horizon.

Decomposing the reallocation channels associated with daily mean temperature beyond 31°C, column 1 shows that 54% (0.14 percentage points) of manufacturing workers laid off due to extreme heat find a formal-sector manufacturing employer in the same municipality within 36 months. Limited intersectoral and interregional reallocation exists for manufacturing workers laid off due to heat shocks. Reallocation to the formal agricultural sector in the same municipality is statistically significant though economically smaller (8%). Based on columns 2, 4, 5, 6, other reallocation channels are economically small and not statistically significant at the 5% level. Figures 12, 13 and 14 present visualizations of these results, where the left panels show transitions within the same municipalities across sectors, and the right panels show interregional worker reallocation.

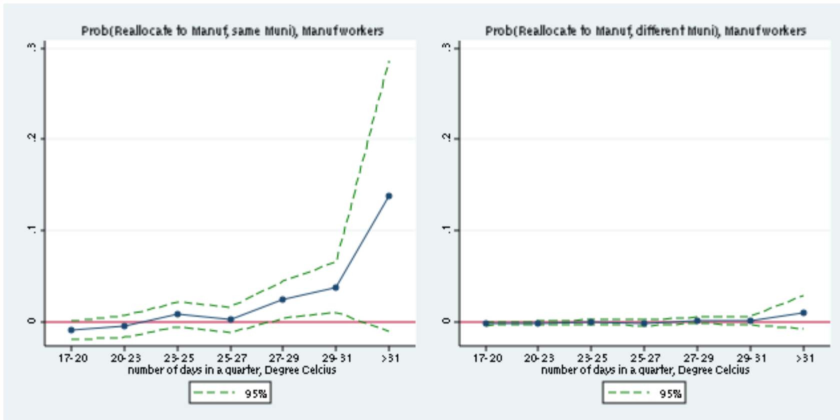
Figure 15 and column 7 in Table 1 illustrate the salience of failure to reallocate for manufacturing workers laid off due to heat shocks. A significant 24.3% of all manufacturing workers who experienced heat-related layoffs fail to find any formal sector employment within 36 months. Swapping a day with daily mean temperatures below 17°C for one with daily mean temperatures beyond 31°C increases the propensity of manufacturing layoff followed by failure to reallocate within 3 years by 0.06 percentage points. This is equivalent to 0.8% of the baseline layoff propensity.

Table 1: Quarterly heat shocks and manuf. worker reallocation, all seasons

	(1) Manu-s b/se	(2) Manu-d b/se	(3) Agr-s b/se	(4) Agr-d b/se	(5) Serv-s b/se	(6) Serv-d b/se	(7) Failure b/se	(8) Tot. layoff b/se
Temp(17-20)	-0.00946*	-0.00220**	-0.00194**	-0.00190**	-0.00107	-0.00226*	-0.00180	-0.02064**
	(0.005)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.008)
Temp(20-23)	-0.00526	-0.00154	-0.00089	-0.00143	0.00010	-0.00240	-0.00101	-0.01243
	(0.006)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.011)
Temp(20-25)	0.00799	-0.00022	-0.00052	0.00081	0.00245*	-0.00245	-0.00014	0.00793
	(0.007)	(0.001)	(0.001)	(0.001)	(0.001)	(0.002)	(0.002)	(0.012)
Temp(25-27)	0.00198	-0.00118	-0.00081	0.00015	0.00146	0.00039	0.00253	0.00451
	(0.007)	(0.002)	(0.001)	(0.001)	(0.002)	(0.002)	(0.003)	(0.013)
Temp(27-29)	0.02413**	0.00166	0.00117	0.00336**	0.00320	0.00628***	0.00380	0.04359**
	(0.010)	(0.002)	(0.001)	(0.002)	(0.002)	(0.002)	(0.003)	(0.017)
Temp(29-31)	0.03784***	0.00106	0.00420**	0.00454*	0.00478	0.00855***	0.01252**	0.07350***
	(0.014)	(0.002)	(0.002)	(0.002)	(0.003)	(0.003)	(0.005)	(0.024)
Temp(>31)	0.13816*	0.01057	0.02177***	0.00536	0.00705	0.00818	0.06142*	0.25250**
	(0.075)	(0.009)	(0.007)	(0.003)	(0.006)	(0.008)	(0.032)	(0.127)
N	16322039	16322039	16322039	16322039	16322039	16322039	16322039	16322039
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	**Meso**							
Other FEs	**Quarter × State, State × Year, Quarter × Year, Prod × Quarter, Prod × Year, Prod × State**							

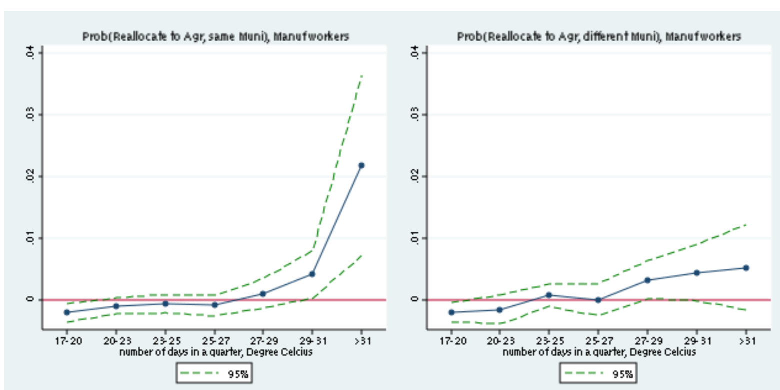
Manufacturing Reallocation, All Seasons—Following Equation 3, the dependent variable Y^p_{ijmt} is the binary variable for whether the worker belongs to a particular postlayoff category, p. The independent variables are the numbers of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The outcomes for Columns 1–8 are (1)failure to reallocate to any formal employer, within 36 months. (2)probability of total layoffs (3)reallocate to the manufacturing sector, in the same municipality, within 36 months; (4) reallocate to the manufacturing sector, in a different municipality, within 36 months; (5) reallocate to the agricultural sector, in the same municipality, within 36 months; (6) reallocate to the agricultural sector, in a different municipality, within 36 months; (7) reallocate to the service/primary sector, in the same municipality, within 36 months; (8) reallocate to the service/primary sector, in a different municipality, within 36 months. All regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry, and municipality fixed effects, along with other weather covariates and a rich set of firm- and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level. *** Significant at 1%, ** 5%, * 10%.

Figure 12: Quarterly heat shocks and manufacturing workers layoff, with reallocation to manufacturing within 36 months



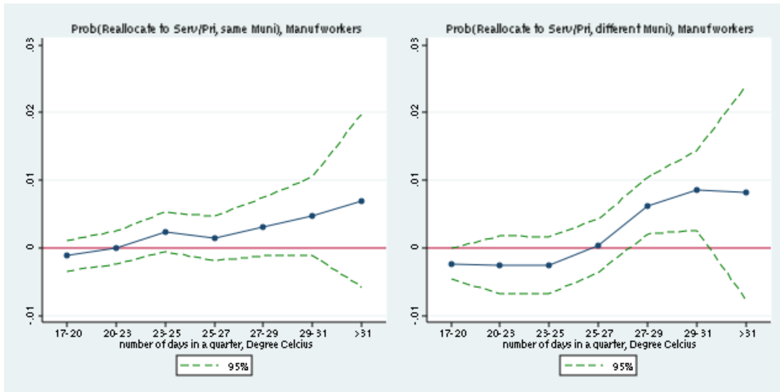
Manufacturing Reallocation, All Seasons—Following Equation 3, the dependent variable Y_{ijmt}^{p} is the binary variable for whether a worker belongs to a particular postlayoff category p. The independent variables are the number of days in a quarter with daily mean temperature in a specific range, $Tempbin_{m,t}^{k}$. The "<17°C" bin is the omitted category. The outcomes are (Left Panel) Reallocate to the manufacturing sector in the same municipality, within 36 months and (Right Panel) Reallocate to the manufacturing sector in a different municipality within 36 months. All regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry, and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

Figure 13: Quarterly heat shocks and manufacturing workers layoff, with reallocation to agriculture within 36 months



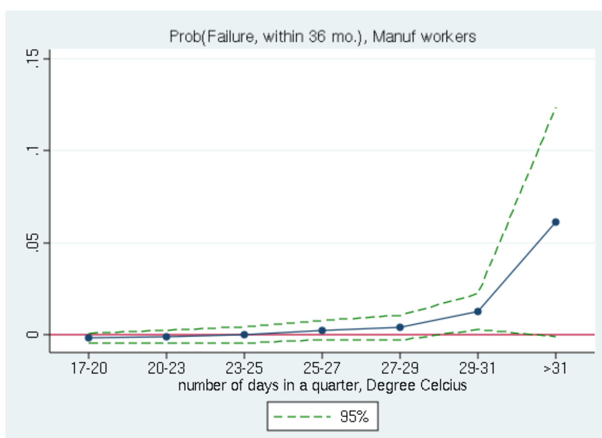
Manufacturing Reallocation, All Seasons—Following Equation 3, the dependent variable Y_{ijmt}^{p} is the binary variable for whether the worker belongs to a particular postlayoff category p. The independent variables are the number of days in a quarter with daily mean temperatures in a specific range, $Tempbin_{m,t}^{k}$. The "<17°C" bin is the omitted category. The outcomes are (Left Panel) Reallocate to the agricultural sector in the same municipality within 36 months and (Right Panel) Reallocate to the agricultural sector in a different municipality within 36 months. All regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry, and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

Figure 14: Quarterly heat shocks and manufacturing workers layoff, with reallocation to Services/Primary within 36 months



Manufacturing Reallocation, All Seasons—Following Equation 3, the dependent variable Y_{ijmt}^{p} is the binary variable for whether a worker belongs to a particular postlayoff category p. The independent variables are the number of days in a quarter with daily mean temperatures in a specific range, $Tempbin_{m,t}^{k}$. The "<17°C" bin is the omitted category. The outcomes are (Left Panel) Reallocate to the services sector in the same municipality within 36 months and (Right Panel) Reallocate to the services sector in a different municipality within 36 months. All regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry, and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

Figure 15: Quarterly heat shocks and manufacturing workers layoff: failure to reallocate within 36 months



Manufacturing Reallocation Failure, All Seasons—Each point estimate reflects an individual regression coefficient, β_k, following Equation 3, where the dependent variable is the binary outcome on whether the worker experiences a layoff followed by failure to reallocate within 36 months. The independent variables are the number of days in a quarter with daily mean temperature in a specific range, $Tempbin_{m,t}^{k}$. The "<17°C" bin is the omitted category. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry, and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level.

A number of reasons could explain this high rate of failure to reallocate due to heat shocks. First, after layoffs, other employers may take it as a signal that the worker is a low type and are therefore reluctant to hire. However, this alone does not seem sufficient to explain the high rate of prolonged failure to reallocate even in another sector or municipality within 3 years. Papers examining labor reallocation after trade liberalization[15] suggest that intersectoral reallocation frictions are much more pronounced in developing countries such as Brazil relative to developed countries such as the U.S. Compared with more permanent trade liberalization, here I show that even transitory temperature shocks lead to significant failure to reallocate, possibly due to frictions in the job rematching process.

Third, transitioning to informality could be an important aspect. Workers not reallocating to another formal-sector job after heat-related layoff could be either unemployed or informally employed. Dix-Carneiro and Kovak (2017b) find that the informal sector is an important absorber of formal workers laid off during trade liberalization. Formal jobs are generally considered to be of higher quality, offering more benefits and greater labor production than informal jobs (La Porta and Sheleifer, 2014). Transitioning to the informal sector under extreme heat shocks could have important worker-welfare implications; an area for future research.

Understanding worker reallocation better quantifies the full cost of climate change for the labor market. Especially in developing countries, the long-term formal labor-market "scarring" associated with heat shocks likely implies more pronounced individual welfare losses. Finally, failure to reallocate happens for both growing and nongrowing season heat shocks. Details appear in Appendix B.

[15] Dix-Carneiro (2014), Goldberg and Pavcnik (2007), Autor et al. (2014).

6 Heterogeneity

Having examined mechanisms and labor reallocation, I now turn to the distributional impact of temperature shocks, identifying the most vulnerable groups in the manufacturing workforce. In addition to the worker-level characteristics in RAIS, I further link variables from the *Dictionary of Occupation Titles (DOT)* to study heterogeneity by occupation-task intensity.

Meta-analysis (Hancock et al., 2007) in the ergonomics literature suggests that thermal stress has the highest impact on psychomotor and motor tasks, and the lowest impact on cognitive skills. In more routine-manual task-intensive occupations, workers' heterogeneous sensitivity to heat may also be better revealed. So the hypothesis is that through the direct labor-productivity channel, individual employment effects are significantly higher for workers in routine-manual-intensive occupations.

6.1 Empirical Strategy

I follow Autor, Levy, and Murnane (2003) in using data from the DOT to construct occupational task-intensity measures for the U.S. Census Occupational Codes. To match the U.S. Census Occupational Codes to the Brazilian Occupational codes, I first concord across time using data provided by Autor and Dorn (2013), and then map the 2000 U.S. Census Occupational Codes to the International Standard Classification of Occupations (ISCO-88), provided by the Center for Longitudinal Studies in UCL. Finally, the concordance from ISCO-88 to the Brazilian occupational codes CBO is by Muendler et al. (2004). Assuming that Brazil and the U.S. share similar relative task intensity across occupations, I obtain an index for routine-manual task intensity (RMTI) based on the DOT measure of *Finger Dexterity* (Autor, Levy and Murnane, 2003).

Table 2 gives some common examples of occupations (CBO, 3-digit) in RAIS with the highest and lowest measures of routine-manual-task intensity. Highly routine manual task-intensive occupations such as fabric treating and weavers require more motor or psychomotor skills, whereas low routine-manual-task occupations require more cognitive skills.

Table 2: Examples of occupations by RMTI

Occupations: Routine-manual task intensity	
High	**Low**
Fabric treating, printing workers	Mathematicians and actuaries
Spinners, twisters, and related workers	Production and research managers
Lace makers, weavers, dyers,	Machine maintenance mechanics
Dressmakers	Cabinet makers
Telephone, telegraph operators,	Plastic product workers

Based on Brazilian CBO three-digit occupational codes in RAIS.

The estimation framework follows Equation 4 and allows for heterogeneous impact along a variety of worker and plant attributes:

$$\begin{aligned} Y_{ijmt} = \sum \beta_{1k} RMTI_{it} * Tempbin^{k}_{m,t} + \sum \beta_{2k} Z_{it} * Tempbin^{k}_{m,t} + \sum \beta_{3k} * Tempbin^{k}_{m,t} \\ +\beta_{40} RMTI_{it} * Hum_{m,t} + \beta_{41} Z_{it} * Hum_{m,t} + \beta_{50} RMTI_{it} * Rain_{m,t} + \beta_{51} Z_{it} * Rain_{m,t} \\ +f(Rain_{m,t}, Hum_{m,t}) + \alpha_1 Z_{it} + \theta_{qy} + \theta_{yr} + \theta_{qr} + \Phi_{yj} + \Phi_{qj} + \Phi_{rj} + \tau_m + \epsilon_{ijmt} \end{aligned} \tag{4}$$

Y_{ijmt} is the binary outcome for worker layoff. Weather variables on temperature, rainfall, and humidity are defined as before. $RMTI_{it}$ measures worker i's occupational routine-manual-task intensity. Z_{it} is a vector of worker-level covariates including wage, gender, tenure, and size of the plant. Both $RMTI_{it}$ and Z_{it} are standardized. X_{it} are other worker or plant-level controls. Fixed effects are included at the Quarter*Year, Year*State, Quarter*State, Industry*Year, Industry*Quarter, State*Industry, and Municipality level. Standard errors are clustered at the mesoregion-level.

6.2 Results

The key coefficients of interest are β_{1k} and β_{2k}, capturing the differential impact of heat shocks interacting with worker attributes on initial occupational-task intensity, wage, gender, plant size, and tenure. Table 3 presents the key coefficients focusing on the interaction with the highest temperature bin ($> 31°$C). I separately examine heterogeneous effects in the nongrowing seasons and in the full sample.

Column 1 shows the estimates for manufacturing worker layoff during the nongrowing seasons, where only the direct labor productivity channel is at work. Here the hypothesis is that as temperatures increase, labor productivity in more routine-manual-intensive tasks will see a larger decrease. Consistent with the ergonomics literature on thermal stress, workers in routine-manual-task-intensive occupations are more likely to experience heat-related layoff. Having a routine-manual-task-intensity measure of one standard deviation beyond the mean increases the effect of an additional extreme heat day by 0.27 percentage points. We also see that the impact of heat shocks are more pronounced for those with less tenure at the plant, which could indicate that workers laid off are more temporary or have lower labor force attachment.

Table 3: Manufacturing layoffs: Worker-level heterogeneity

	(1) layoff b/se	(2) layoff b/se
Temp(>31)	0.0271	0.1037
	(0.092)	(0.072)
RMTI*Temp(>31)	0.2685**	0.0625
	(0.103)	(0.077)
Tenure*Temp(>31)	-0.1443*	-0.1162*
	(0.083)	(0.062)
Observations	1061664	14437797
Subsample	NGSeasons	Full
Clustering	**meso**	
Other FEs	**Quarter*State, State*Year, Quarter*Year, Prod*Quarter, Prod*Year, Prod*State**	
Y(mean)	6.304	6.422

Manufacturing Labor Market, Heterogeneity—Following Equation 3, the dependent variable Y^p_{ijmt} is the binary variable for worker layoff. The independent variables, "RMTI $\times Tempbin^k$," are the worker's occupational routine-manual task intensity (normalized), interacted with the numbers of days in a quarter with daily mean temperature within a specific range k. The "$< 17°C$" bin is the omitted category. All regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry, and municipality fixed effects, along with weather covariates and a rich set of firm- and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level. *** Significant at 1%, ** 5%, * 10%.

In the full sample presented in column 2, a differential effect no longer emerges according to occupational routine-manual-task intensity. Because in the full sample manufacturing workers are laid off from a combination of direct labor productivity and indirect agricultural channels, a pronounced differential impact is unlikely to occur by occupation. Finally, it is important to note that the source of heterogeneity is consistent with, but not limited to, the direct labor productivity channel. Differential coverage of climate controls in the same establishment, observed in Indian diamond-processing factories by Somanathan et al. (2014), for example, could also explain this heterogeneity. Alternatively, if occupations differ in the ease with which workers can switch to the informal sector, one could also observe a similar differential impact by occupational-task intensity. Overall, heterogeneity analysis in this section informs identification of vulnerable groups in the manufacturing workforce most affected by heat shocks, and reveals potential distributional impact.

7 Additional Evidence

In Section 4, I briefly reviewed some possible scenarios in which transitory shocks could lead to significant increases in manufacturing layoff. The simplest explanation is if firing and hiring costs are not prohibitively high, which I test here using Bartik-type shocks in output. Other relevant factors include asymmetrical adjustment costs leading to concave hiring rules (Ilut et al., 2018), worker heterogeneity in heat sensitivity, or willingness to exert effort under heat exposure (Graff Zivin and Neidell, 2014), and downward nominal wage rigidity. In this section, I also explore the role of nominal wage rigidity using historic inflation spikes in Brazil.

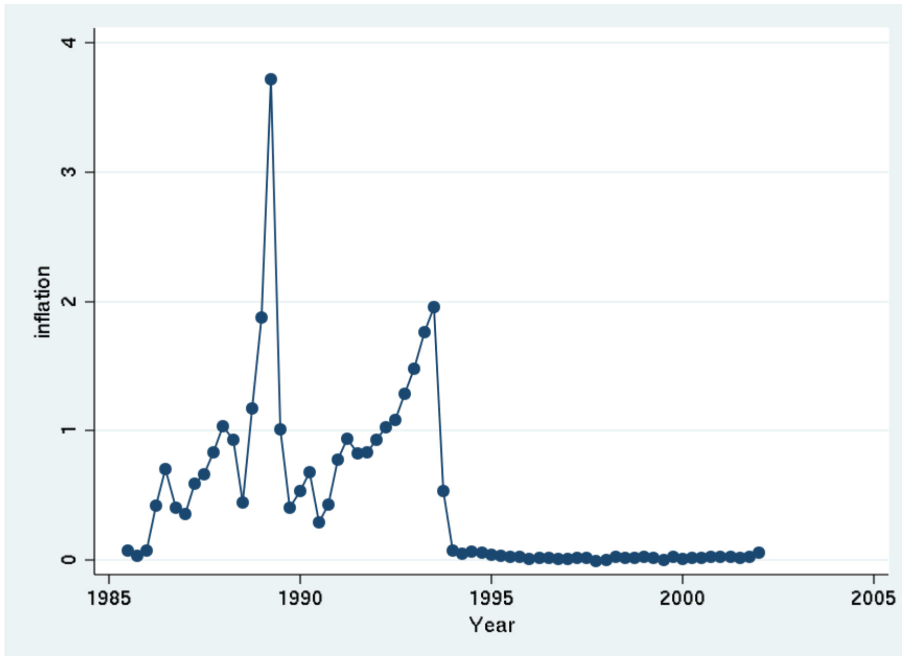
7.1 The Role of Nominal Wage Rigidity

Brazil experienced high and volatile episodes of inflation after the 1960s. I exploit the inflation spike in the 1990s to check if downward nominal wage rigidity could cause the employment effect of heat shocks. Intuitively, firms may choose to lay off workers when wages are rigid downwards. During periods of high inflation, however, real wages are effectively lower, leading to smaller employment effects of extreme heat shocks. The effect of inflation would not be present if wages are always indexed. Throughout 1985–1999, however, the Brazilian government periodically froze wages and stopped indexation to lower inflation expectations (Duryea and Arends-Kuenning, 2003).

$$\begin{aligned} Y_{ijmt} = \sum \beta_{1k} Inflation_t * Tempbin^k_{m,t} + \sum \beta_{2k} * Tempbin^k_{m,t} + \beta_3 Inflation_t * Hum_{m,t} \\ + \beta_4 Inflation_t * Rain_{m,t} + f(Rain_{m,t}, Hum_{m,t}) + \theta_{qy} + \theta_{yr} + \theta_{qr} + \Phi_{yj} + \Phi_{qj} + \tau_m + \epsilon_{ijmt} \end{aligned} \quad (5)$$

Y_{ijmt} is the binary outcome for worker layoff. Weather variables of temperature, rainfall, and hu-

Figure 16: Quarterly Brazilian inflation index



This chart shows quarterly inflation measured by the Brazilian national price index, *INPC*, from 1985 to 2002. Raw data are made public by Marc Muendler, http://econweb.ucsd.edu/muendler/.

midity are defined as before. $Inflation_t$ is quarterly inflation measured by the Brazilian national price index, *INPC*.[16] Fixed effects are included at the Quarter*Year, Year*State, Quarter*State, Industry*Year, Industry*Quarter, State*Quarter, and Municipality level. Standard errors are clustered at the mesoregion level.

Figure 16 plots the "hyperinflation" period in Brazil using the quarterly inflation index from 1986 to 2002. I match the data from 1990 to 2000 with RAIS and exploit the inflation spike from 1990 to 1995. I interpose the inflation index with heat shocks to see whether the employment impact of extreme heat is smaller during high inflation. My intuition indicates that the employment effect of a labor productivity drop is larger when nominal wages are rigid downward. By effectively lowering real wages, higher inflation dampens the effect on worker layoff. Kaur (2018) pioneered this test and found a similar mechanism in Indian village labor markets.

Table 4 shows the results of nongrowing versus growing seasons. Here I focus on the effect of an

[16] These data are made public by Marc Muendler, http://econweb.ucsd.edu/muendler/.

Table 4: Heat shocks and nominal wage rigidity: Growing vs. nongrowing seasons

	(1) Layoff b/se	(2) Layoff b/se
Temp(>31)	1.3946***	0.1245**
	(0.358)	(0.049)
Temp(>31) × Inflation	0.2678	-0.0956**
	(0.278)	(0.037)
Humidity	-0.0113	-0.0047
	(0.056)	(0.011)
Humidity × Inflation	-0.0775	-0.0100
	(0.068)	(0.016)
Observations	1,377,060	16,182,508
Municipality FE	Yes	Yes
Subsample	NGSeasons	GSeasons
Clustering	meso	meso
Y (mean)	7.17	7.75

Manufacturing Labor Market, Nominal Wage Rigidity—Following Equation 4, the dependent variable, Y^{p}_{ijmt}, is the binary variable for worker layoff. The key independent variables, $Tempbin^{k}\times$ inflation, are the number of days in a quarter with daily mean temperature within a specific range k, interacted with the quarterly inflation index. The "$< 17°$C" bin is the omitted category. All regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry, and municipality fixed effects, along with weather covariates and a rich set of firm- and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level. *** Significant at 1%, ** 5%, * 10%.

additional extreme heat day, with daily mean temperatures beyond 31 degrees Celsius. Column 1 shows that during nongrowing seasons, swapping a day with daily mean temperatures below 17°C for one with daily mean temperatures beyond 31°C increases the probability of layoff by 1.4 percentage points, or a 19.45% increase of the baseline layoff propensity (7.17 percentage points). The effect does not vary with inflation, suggesting downward nominal wage rigidity is not a dominant cause of the manufacturing layoffs observed in Section 4.2.1. That is, even when the wage floor is flexible, firms still choose to lay off workers under extreme heat during nongrowing seasons. One possibility consistent with this evidence is if workers who are more heat sensitive or who exert less effort when exposed to heat are revealed after heat shocks, they may be laid off regardless of wage rigidity. In contrast, Column 2 shows that layoffs during growing seasons are dampened during high inflation. Intuitively, growing-season layoffs could be caused by lower local demand or higher input price from indirect agricultural channels. Firms are less likely to lay off workers when inflation enables downward real-wage adjustment.

7.2 Bartik Shocks in Output

Whether a significant labor productivity shock caused by heat stress would lead to worker layoff depends on specific labor-market institutions in Brazil. In this subsection, I provide relevant institutional details on hiring and firing costs, and check the ease with which firms lay off workers in the presence of temporary output contraction.

Firms in Brazil in general face moderate firing and hiring costs. In the case of layoffs without a special cause, the firm pays 40% of the accumulated job security fund (FGTS) upon layoff (Menezes-Filho and Muendler, 2011), which is about 0.5 month's salary for the average person being laid off in my sample.[17] The firm's penalty for laying off a worker is around 8–19% of the UI benefit paid to the worker (Van Doornik et al., 2017). However, Almeida and Carneiro (2012) also suggest that due to imperfect enforcement, the de facto cost of firing a worker may be less than it appears on paper.

To check the ease with which firms lay off workers in Brazil, I estimate the impact of Bartik

[17] The median tenure of workers at the time of layoff in my sample is around 15 months.

output shocks on firm employment following an approach similar to Hershbein and Kahn (2018). If layoff decisions respond to the regional share of national changes in output, the firing costs are unlikely to be prohibitively high. I use the full sample data in RAIS to construct regional industry employment weights and the Industrial Physical Production Index from the PIM (IBGE) for industry-specific changes in national output during the years 1992–2000.[18] $\phi_{m,k,\tau}$ stands for the regional industry employment share of industry k in municipality m in a prior year (1989). lnB_{kt} is the log of national output in industry k in year t. The Bartik shock in output for municipality m in year t, ΔB_{mt}, is calculated following Equation 6. I estimate how the probability of worker layoff responds to Bartik shocks in output following the fixed-effect framework in Equation 7.

$$\Delta B_{mt} = \sum^{k} \phi_{m,k,\tau}(lnB_{kt} - lnB_{k,t-1}) \tag{6}$$

$$Y_{ikmt} = \beta_1 \Delta B_{mt} + \alpha_1 X_{it} + \theta_{kt} + \Phi_{ks} + \tau_m + \tau_i + \epsilon_{ikmt} \tag{7}$$

Y_{ijmt} is the binary outcome for worker layoff at the yearly frequency. X_{it} is a vector of worker and plant-level controls. I also include controls for industry growth trends, industry specializations, and municipality and worker fixed effects. Standard errors are clustered at the worker and municipality levels. To examine layoff response to output contraction versus expansion, I look at the subsample where the Bartik shock is negative rather than positive. Table 5 shows that the probability of layoffs responds strongly to annual output contraction and less so to output expansion, consistent with firms having concave hiring rules (Ilut et al., 2018). In particular, a one-percentage-point (relative) regional output reduction leads to a 0.57 percentage point increase in the probability of worker layoff, whereas an output expansion of the same magnitude only leads to a 0.16 percentage point decrease in the propensity of layoff.

[18]The index is not available for 1991.

Table 5: Manufacturing layoff and yearly Bartik shock in output

	(1) Layoff b/se	(2) Layoff b/se
ΔB_{mt}^{output}	-0.5659***	-0.1565**
	(0.153)	(0.075)
Observations	1,488,964	2,537,323
Worker FE	Yes	Yes
Municipality FE	Yes	Yes
Subsample	$\Delta B_{mt} < 0$	$\Delta B_{mt} > 0$
Clustering	**Worker, Municipality**	

Manufacturing Labor Market—Following Equation 6, the dependent variable, Y_{ijmt}, is the binary outcome for worker layoff at the yearly frequency. The independent variable, ΔB_{mt}, is the municipality-level Bartik shock in output (see text for details). All regressions include industry × year, state × industry, worker, and municipality fixed effects, along with a rich set of firm- and worker-level controls. *** Significant at 1%, ** 5%, * 10%.

8 Conclusion

Climate change poses significant challenges to manufacturing labor markets in developing countries, especially given future climate predictions. In this paper, I examine the short- and medium-run employment adjustment margins of heat shocks through individual worker layoff, hiring, and job reallocation. By focusing on heat shocks during the nongrowing seasons of each local labor market in Brazil, I show that the direct labor-productivity channel associated with extreme heat days leads to significant worker layoff. These effects are more pronounced for workers in more routine manual task-intensive occupations. Over time, a significant 24.3% of all manufacturing workers who were laid off due to quarterly heat shocks failed to find another formal job within 36 months, suggesting large worker-level costs over the medium run.

I address several natural extensions in ongoing work. The first is to further understand how climate change affects worker transition into informality and associated implications for worker welfare. Second, I expand work on various adjustment margins that include the firm, industry, and regional perspectives, which helps better explain the adjustment process in general equilibrium. Finally, given more pronounced impact on workers in lower skilled occupations and the large fraction of workers near minimum wage in Brazil, the next step is to quantify how existing social welfare programs interact with climate change and how to better design such programs.

Findings from this research inform a more comprehensive cost assessment of climate-change damages. Worker-level evidence is one step closer to identifying certain groups in the workforce who are more vulnerable to these dramatic environmental changes, and to targeting mechanism-specific interventions. This paper also shows that existing labor-market transitional costs in developing countries could further interact with heat shocks and exacerbate worker welfare loss. Together, this micro-level evidence suggests the importance of incorporating sector, region, and worker-specific estimates of climate-change damages, building on existing tools such as the Integrated Assessment Models (Nordhaus, 2017).

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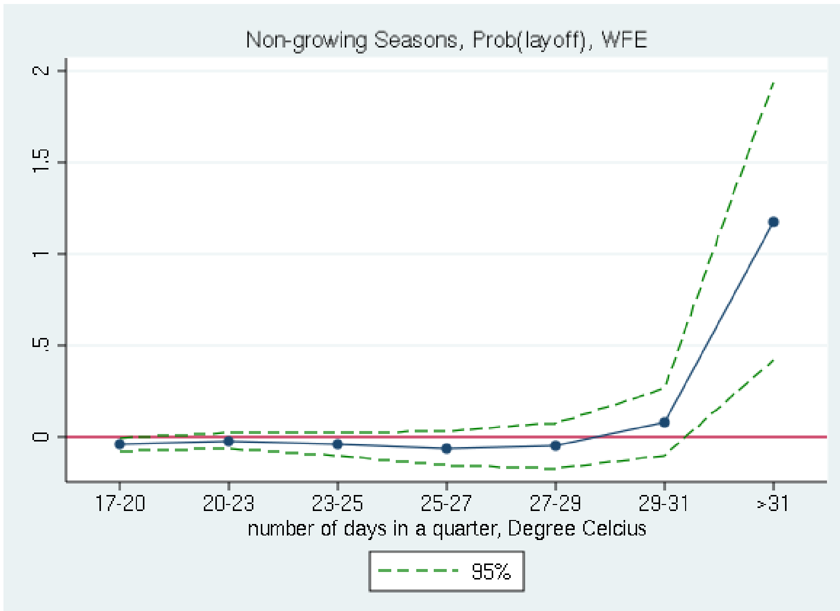
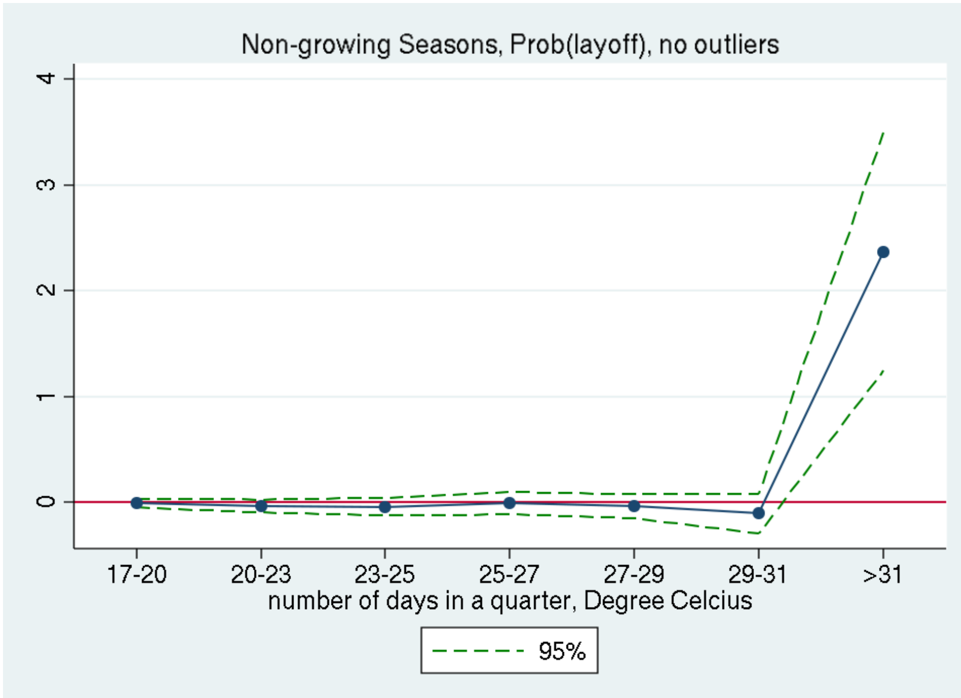
A Additional Figures

Figure A.1: Manufacturing worker layoff: nongrowing seasons, with worker fixed effects and lagged weather shocks



Manufacturing Labor Market, Nongrowing Seasons, Worker FE, Lags - Each point estimate reflects an individual regression coefficient, β_k, following Equation 1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C, *in the nongrowing seasons*. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls. In addition, this specification controls for worker fixed effects and average weather shocks for the past three quarters. All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

Figure A.2: Manufacturing worker layoff: nongrowing seasons, excluding outliers (cooksd)



Manufacturing Labor Market, Nongrowing Seasons, Cook's Distance - Each point estimate reflects an individual regression coefficient, β_k, following Equation 1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. *We drop influential outliers with Cook's distance larger than 4/n, where n is the total number of observations.* The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C, *in the nongrowing seasons*. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls. In addition, this specification controls for worker fixed effects and average weather shocks for the past three quarters. All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

B Additional Tables

Table B.1: Quarterly heat shocks and manuf. worker reallocation, nongrowing seasons

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Manu-s	Manu-d	Agr-s	Agr-d	Serv-s	Serv-d	**Failure**	**Tot. layoff**
	b/se	b/se	b/se	b/se	b/se	b/se	b/se	b/se
Temp(>31)	0.530***	0.053**	0.019***	0.006	0.027**	0.033	**0.283*** **	**0.952*** **
	(0.133)	(0.024)	(0.007)	(0.006)	(0.012)	(0.021)	(0.069)	(0.251)
Decomposition	**55.7%**	5.6%	2.1%	0.6%	2.9%	3.45%	**29.7%**	**100%**
N	16322039	16322039	16322039	16322039	16322039	16322039	16322039	16322039
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	**Meso**							
Other FEs	**Quarter × State, State × Year, Quarter × Year, Prod × Quarter, Prod × Year, Prod × State**							

Manufacturing Reallocation, Nongrowing Seasons—Following Equation 2, the dependent variable Y^p_{ijmt} is the binary variable for whether the worker belongs to a particular postlayoff category, p. The independent variables are the numbers of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The outcomes for Columns 1–7 are (1) reallocate to the manufacturing sector, in the same municipality, within 36 months; (2) reallocate to the manufacturing sector, in a different municipality, within 36 months; (3) reallocate to the agricultural sector, in the same municipality, within 36 months; (4) reallocate to the agricultural sector, in a different municipality, within 36 months; (5) reallocate to the service/primary sector, in the same municipality, within 36 months; (6) reallocate to the service/primary sector, in a different municipality, within 36 months; and (7) failure to reallocate to any formal employer, within 36 months. All regressions include quarter × state, quarter × industry, quarter × year, state × year, industry × year, state × industry, and municipality fixed effects, along with other weather covariates and a rich set of firm- and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the mesoregion level. *** Significant at 1%, ** 5%, * 10%.

C Agricultural Layoff and Hiring: Nongrowing seasons vs. Growing seasons

I briefly examine the formal agricultural labor-market impact to verify the underlying assumption for isolating the direct labor productivity channel. Recall that we identify the direct labor productivity channel by focusing on heat shocks during the nongrowing seasons. A key assumption here is that heat shocks during the nongrowing seasons have no significant impact on agricultural outcomes.

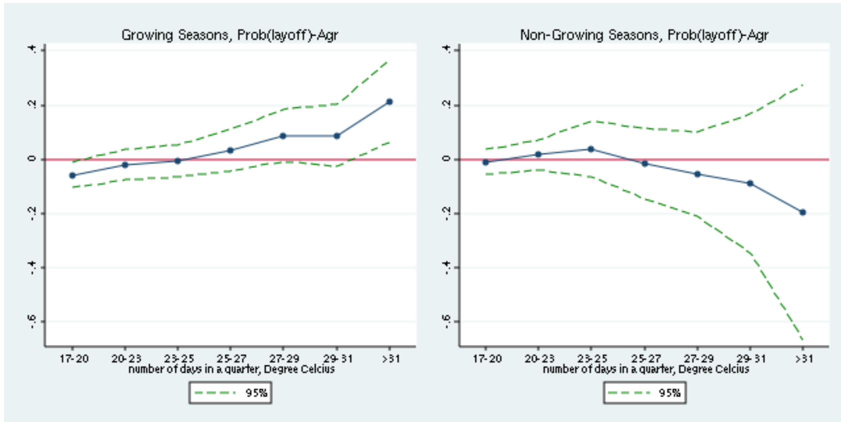
We verify this by looking at agricultural layoff and hiring during growing versus nongrowing seasons. As shown in the left panels of Figure C.1 and Figure C.2, heat shocks during growing seasons increase the propensity of agricultural layoff and reduce the propensity of hiring, consistent with the literature on temperature and crop yield.[19] Since crop yield decreases with temperature, there would be less demand for agricultural workers.

Crucial for our identification assumption, the right panels of Figure C.1 and Figure C.2 show that heat shocks during nongrowing seasons have no significant impact on the agricultural labor market. This is expected if there is little agricultural crop growing activity which is temperature sensitive occurring outside the growing seasons.[20] Together, these results are consistent with the identifying assumption that heat shocks during nongrowing seasons do not operate through agricultural channels. Finally, I do additional robustness check focusing on sugarcane workers only. In Brazil, the sugarcane sector is unionized, 70% formal, and therefore has better coverage in RAIS. The findings are similar (Figure C.3).

[19](Schlenker and Roberts, 2009; Lobell et al., 2011)

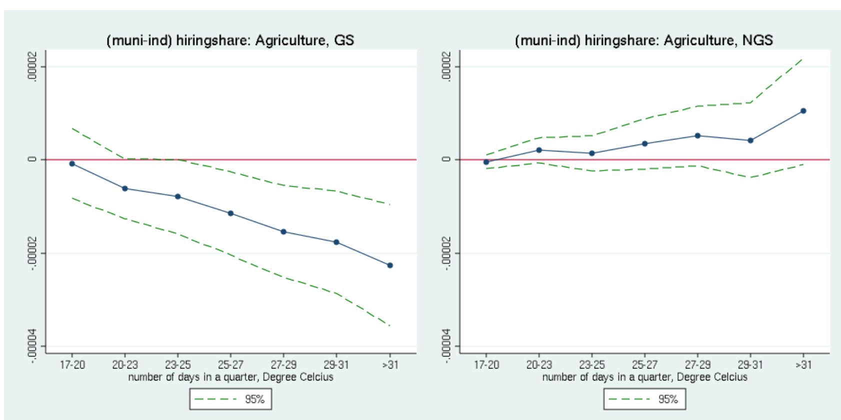
[20]There may still be agricultural workers employed during the nongrowing seasons, engaging in marketing, and looking for opportunities to sale of their crops.

Figure C.1: Quarterly heat shocks and agricultural layoff



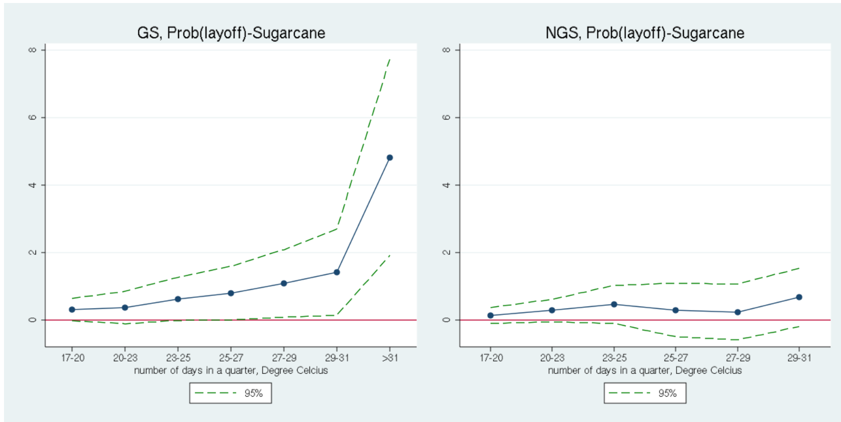
Agricultural Labor Market, Growing seasons versus Nongrowing seasons - Each point estimate reflects an individual regression coefficient, β_k, following Equation 1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls. All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

Figure C.2: Quarterly heat shocks and agricultural hiring



Agricultural Labor Market, Growing seasons versus Nongrowing seasons - Each point estimate reflects an individual regression coefficient, β_k, following Equation 1. The dependent variable is region-industry hiring share, constructed by aggregating the total number of individual accession in each quarter at the municipality-industry level, normalized by each municipality's population in 1999. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the hiring share, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, and other weather covariates (see text for details). Standard errors are clustered at the meso-region level.

Figure C.3: Sugarcane worker layoff: growing versus nongrowing seasons



Sugarcane Labor Market, Growing seasons versus Nongrowing seasons - Each point estimate reflects an individual regression coefficient, β_k, following Equation 1, where the dependent variable is the binary outcome on worker layoff. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The coefficient β_k is interpreted as the estimated impact of one additional day with daily mean temperature in temperature bin k on the propensity of worker layoff, relative to the impact of a day with daily mean temperature less than 17°C. The regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls. All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level.

D Reallocation for Agricultural Workers

Table D.1 shows agricultural worker reallocation post layoff, due to heat shocks during the growing seasons. More intersectoral reallocation happens for agricultural workers, possibly because manufacturing is better represented in the formal sectors. As shown in column 3 and 4 in Table D.1, 54.1% of all heat-related layoffs find another agricultural employment within the same municipality, while 19.7% workers find another agricultural employment in a different municipality, both within three years. Based on column 1 and 2, roughly 16.8% of heat-related agricultural layoffs find the next job in manufacturing, either in the same or a different municipality.

Table D.1: Quarterly Heat Shocks and Agr. Worker Reallocation, GS

	(1) Manu-s b/se	(2) Manu-d b/se	(3) Agr-s b/se	(4) Agr-d b/se	(5) Serv-s b/se	(6) Serv-d b/se	(7) Failure b/se	(8) Tot. layoff b/se
Temp(17-20)	0.00098	-0.00006	-0.01737	-0.01957***	-0.00507***	-0.01247***	-0.01427**	-0.06783**
	(0.002)	(0.003)	(0.016)	(0.007)	(0.002)	(0.003)	(0.007)	(0.032)
Temp(20-23)	-0.00102	0.00091	0.00112	-0.00768	-0.00499***	-0.00449	-0.01079	-0.02694
	(0.003)	(0.004)	(0.017)	(0.010)	(0.002)	(0.005)	(0.009)	(0.040)
Temp(23-25)	0.00404	0.00641	0.02841	-0.00115	-0.00619**	-0.00371	-0.01274	0.01506
	(0.003)	(0.004)	(0.019)	(0.010)	(0.002)	(0.005)	(0.009)	(0.043)
Temp(25-27)	0.00785**	0.01090**	0.05281**	0.01085	-0.00350	0.00061	-0.00215	0.07736
	(0.004)	(0.005)	(0.026)	(0.011)	(0.003)	(0.006)	(0.011)	(0.057)
Temp(27-29)	0.01351**	0.02196***	0.11323***	0.03619**	0.00072	0.00732	0.01289	0.20582***
	(0.005)	(0.006)	(0.038)	(0.015)	(0.003)	(0.008)	(0.014)	(0.077)
Temp(29-31)	0.02148**	0.02493***	0.13927***	0.03694**	-0.01006	0.00413	0.01723	0.23393**
	(0.010)	(0.007)	(0.052)	(0.018)	(0.007)	(0.009)	(0.017)	(0.098)
Temp(>31)	**0.02149***	**0.04504****	**0.21399****	**0.07791****	**0.00006**	**0.01003**	**0.02727**	**0.39579****
	(0.012)	(0.011)	(0.076)	(0.023)	(0.007)	(0.012)	(0.027)	(0.136)
N	1677744	1677744	1677744	1677744	1677744	1677744	1677744	1677744
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	**Meso**							
Other FEs	**Quarter*State, State*Year, Quarter*Year, Prod*Quarter, Prod*Year, Prod*State**							

Agricultural Reallocation, Growing Seasons - Following equation 2, the dependent variable Y^p_{ijmt} is the binary variable for whether the worker belongs to a particular post-layoff category p. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^k_{m,t}$. The "<17°C" bin is the omitted category. The outcome for column 1-7 are: (1) Reallocate to the manufacturing sector, in the same municipality, within 36 months (2) Reallocate to the manufacturing sector, in a different municipality, within 36 months (3) Reallocate to the agricultural sector, in the same municipality, within 36 months (4) Reallocate to the agricultural sector, in a different municipality, within 36 months (5) Reallocate to the service/primary sector, in the same municipality, within 36 months (6) Reallocate to the service/primary sector, in a different municipality, within 36 months (7) Failure to reallocate to any formal employer, within 36 months. All regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level. *** Significant at the 1 percent, ** 5 percent, * 10 percent.

The majority of the Brazilian agricultural workers are informal and therefore not covered in RAIS. Alternatively, I focus only on sugarcane workers who are highly unionized and better represented in the formal sector (Table D.2). We see around 72% sugarcane workers reallocate within the agricultural sector in the same or a different municipality. 7.2% and 7.3% reallocate to manufacturing or services in a different municipality. Although failure to reallocate is not significant for the full agricultural sample, a significant 11.2% sugarcane workers fail to find any formal sector employment within the next three years. This failure rate is much lower compared to manufacturing. Out of the many possible explanations, we might expect agricultural workers to be more willing to switch to manufacturing and services due to a higher wage premium, while manufacturing workers may be less willing to switch to agriculture.

Table D.2: Quarterly Heat Shocks and Sugarcane Worker Reallocation, GS

	(1) Manu-s b/se	(2) Manu-d b/se	(3) Agr-s b/se	(4) Agr-d b/se	(5) Serv-s b/se	(6) Serv-d b/se	(7) Failure b/se	(8) Tot. layoff b/se
Temp(17-20)	0.03543**	0.01736	0.05293	-0.01565	-0.00238	0.00486	-0.00772	0.08482
	(0.015)	(0.017)	(0.067)	(0.030)	(0.006)	(0.009)	(0.011)	(0.108)
Temp(20-23)	-0.01328	0.01325	0.10262	0.03931	-0.00665	0.01228	0.00648	0.15401
	(0.021)	(0.020)	(0.075)	(0.046)	(0.007)	(0.013)	(0.019)	(0.157)
Temp(23-25)	0.01509	0.04480**	0.19791*	0.05176	-0.02086	0.02409	0.01424	0.32702*
	(0.022)	(0.021)	(0.104)	(0.051)	(0.013)	(0.018)	(0.024)	(0.185)
Temp(25-27)	0.00988	0.04089	0.22959*	0.08187	-0.01048	0.02403	0.02206	0.39783*
	(0.023)	(0.031)	(0.119)	(0.053)	(0.009)	(0.019)	(0.030)	(0.227)
Temp(27-29)	0.01994	0.09371**	0.41827**	0.16739**	0.00105	0.04552*	0.05445	0.80034**
	(0.033)	(0.042)	(0.161)	(0.075)	(0.011)	(0.026)	(0.042)	(0.320)
Temp(29-31)	0.04807	0.13761**	0.65303***	0.19977**	0.01136	0.04100	0.06194	1.15278***
	(0.047)	(0.057)	(0.216)	(0.099)	(0.024)	(0.031)	(0.067)	(0.421)
Temp(>31)	0.27051	0.39336***	3.01420*	0.91793***	-0.15311	0.39783***	0.61068***	5.45141***
	(0.172)	(0.144)	(1.803)	(0.185)	(0.102)	(0.111)	(0.226)	(1.985)
N	1677744	1677744	1677744	1677744	1677744	1677744	1677744	1677744
Municipality FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Clustering	**Meso**							
Other FEs	**Quarter*State, State*Year, Quarter*Year, Prod*Quarter, Prod*Year, Prod*State**							

Sugarcane Worker Reallocation, Growing Seasons - Following equation 2, the dependent variable Y^{p}_{ijmt} is the binary variable for whether the worker belongs to a particular post-layoff category p. The independent variables are the number of days in a quarter with daily mean temperature within a specific range, $Tempbin^{k}_{m,t}$. The "<17°C" bin is the omitted category. The outcome for column 1-7 are: (1) Reallocate to the manufacturing sector, in the same municipality, within 36 months (2) Reallocate to the manufacturing sector, in a different municipality, within 36 months (3) Reallocate to the agricultural sector, in the same municipality, within 36 months (4) Reallocate to the agricultural sector, in a different municipality, within 36 months (5) Reallocate to the service/primary sector, in the same municipality, within 36 months (6) Reallocate to the service/primary sector, in a different municipality, within 36 months (7) Failure to reallocate to any formal employer, within 36 months. All regressions include quarter*state, quarter*industry, quarter*year, state*year, industry*year, state*industry and municipality fixed effects, other weather covariates, and a rich set of firm and worker-level controls (see text for details). All coefficients are multiplied by 100. Standard errors are clustered at the meso-region level. *** Significant at the 1 percent, ** 5 percent, * 10 percent.

E Theory Appendix

I begin with a model where firms are monopolistically competitive and derive how firms with different productivity draws optimally choose their factor input under temperature shocks. To echo the empirical facts on within-industry firm productivity and factor intensity, I adopt a production function developed by Burstein and Vogel (2016) where more productive firms are also less labor intensive.

To the original production function, I add an element of temperature shocks faced by the firm modeled as a change in labor productivity. This modeling choice is motivated by the empirical literature on thermal stress and labor productivity impact discussed in the main paper.

E.1 Temperature Shocks

Temperature shocks influence manufacturing production through changes in labor productivity. In this section, I assume that heat exposure negatively impact production (or unskilled) workers more than skilled workers, and labor productivity more than capital productivity.

Specifically, temperature enters the firm's production function through labor productivity $F(T)$, which is modeled flexibly to allow for possible nonlinear relationship between temperature and labor productivity. Numerous empirical studies suggest that $F(T)$ is single-peaked, with a global maximum at the ideal body temperature point t_0, although the value of t_0 could differ by population and geographic characteristics.

E.2 Demand

As in Melitz (2003), the representative consumer has CES utility over a continuum of goods, each produce by a single firm, indexed by ω.

$$U = [\int_{\omega \in \Omega} q(\omega)^{\sigma} d\omega]^{1/\sigma} \tag{8}$$

Consumption varieties has the elasticity of substitution σ. Here I assume that consumption goods are substitutes, i.e. $\sigma > 1$. Solving the consumer's utility maximization problem, we can derive the demand function for an individual variety ω, given by $q(\omega) = p(\omega)^{-\sigma} R P^{\sigma-1} = \Gamma p(\omega)^{-\sigma}$.

R is the national income, and P is the national price index. For now in the partial equilibrium analysis, both are assumed to be fixed and taken as exogenous under regional temperature shocks. In addition, I assume that there's a numeraire good in an outside agricultural sector which fixes wage.

E.3 Production

Firms face monopolistic competition and each produces variety (ω, j) where j is the industry index. There are two factors of production, capital k, and labor l. Let ρ denote the elasticity of substitution between factors. I assume for now that factors are substitutes with the elasticity $\rho > 1$. Each industry j faces a sector total factor productivity $A(j)$.

In order to produce, firms have to incur a fixed cost f. Upon entry, each firm has a productivity draw, from an i.i.d. distribution of random variables $z(\omega, j) = u^{-\theta}$, where u is exponentially distributed with mean and variance 1.

To capture the empirical fact that more productive firms are also less labor intensive, I employ a production function with "capital-biased productivity" proposed by Burnstein and Vogel (2016).

$$y = A(j)z(\omega, j) * [\alpha_j^{\frac{1}{\rho}}(z(\omega, j)^{\frac{\phi}{2}}k)^{\frac{\rho-1}{\rho}} + (1-\alpha_j)^{\frac{1}{\rho}}(z(\omega, j)^{\frac{-\phi}{2}}F(T)l)^{\frac{\rho-1}{\rho}}]^{\frac{\rho}{\rho-1}} \tag{9}$$

α_j is the industry input elasticity. $z(\omega, j)$ represents within industry productivity. Both $\alpha_j \in (0, 1)$ and $\phi \in [-2, 2]$ shape the labor-intensity of production.

In addition to the firm's initial productivity draw $z(\omega, j)$, temperature shapes labor productivity through $F(T)$. Beyond the ideal body temperature point, increases in temperature reduces effective labor. The production function given in equation 9 deviates from the classic CES production function by incorporating the "capital-biased productivity" mechanism, assuming $\phi(\rho - 1) > 0$. This is reflected in the equilibrium condition that firms with a higher productivity draw $z(\omega, j)$ also has a higher capital to labor ratio.

E.4 Price-Setting

The production function given in equation 9 has constant returns to scale and a constant variable cost $c(r, w, z)$. The firm therefore sets its price p, maximizing profit according to: $pq(\omega) - cq(\omega) - f = \Gamma p^{1-\sigma} - c(r, w, z)p^{-\sigma} - f$. From the profit function, we can derive the optimal price: $p(\omega)^* = \frac{\sigma}{\sigma-1}c$. As in the Melitz model, we also have that optimal price is a constant mark-up of the constant variable cost.

It is worth noting that in the monopolistic competition setting with CES preferences the price of a variety (ω, j) does not depend on the number of competing firms in the market. The price elasticity of demand for any variety also does not respond to changes in the number or prices of competing varieties.

For now, I continue the baseline model with the settings in Melitz (2003), the optimal quantity produced is:

$$q(\omega) = \Gamma(\frac{\sigma}{\sigma - 1}c)^{-\sigma} = Gc^{-\sigma} \tag{10}$$

where $G = \Gamma(\frac{\sigma}{\sigma-1})^{-\sigma} = RP^{\sigma-1}(\frac{\sigma}{\sigma-1})^{-\sigma}$ and the firm's profit is $\pi(\omega)^* = \frac{1}{\sigma-1}Gc^{1-\sigma} - f$.

E.5 Expenditure Minimization

To derive the firm's optimal factor choices, I solve the following expenditure minimization problem. A firm in industry j, producing variety ω, faces the following cost minimization problem upon entry:

$$\min_{k,l} e = wl + rk + f, s.t : y = x \tag{11}$$

From the equilibrium condition of the cost minimization problem, I derive the capital-to-labor ratio equation which illustrates the "capital-biased productivity" mechanism in the production function.

$$\frac{k(\omega, j)}{l(\omega, j)} = (\frac{r}{w})^{-\rho}\frac{\alpha_j}{1 - \alpha_j}z(\omega, j)^{\phi(\rho-1)}F(T)^{1-\rho} \tag{12}$$

Here we see that when $\phi(\rho - 1) > 0$ as assumed before, firms with a higher productivity draw

$z(\omega, j)$ will have a higher capital to labor ratio in equilibrium, thus productivity is capital-biased. Assuming factors are substitutes, or $\rho > 1$, we see that the firm's capital to labor ratio increases as temperature shocks decrease labor productivity. The equilibrium-level of capital to labor ratio is shaped by both industry parameters, ϕ and ρ, as well as the within industry firm-specific productivity, $z(\omega, j)$, which is the key parameter for comparative statics and empirical analysis.

E.6 The Zero Profit Cutoff Condition

Next, I look at how temperature shocks impact firm exit and regional productivity cutoffs. From optimal price-setting, we know that each firm has the maximized profit $\pi(z) = \frac{1}{\sigma-1} G c(z,T)^{1-\sigma} - f$. We can show that $c(z,T)$ is monotonically decreasing in z, and monotonically increasing in T.

For any fixed temperature T, there exist a unique productivity cutoff z^* such that $\pi(z^*) = 0$, so that any firm with a productivity draw $z < z^*$ will immediately exit and never produce. The zero cutoff productivity z^* is given by the condition:

$$c(z^*) = [\frac{f(\sigma-1)}{RP^{\sigma-1}(\frac{\sigma}{\sigma-1})^{-\sigma}}]^{\frac{1}{1-\sigma}} = [\frac{f(\sigma-1)}{G}]^{\frac{1}{1-\sigma}} \tag{13}$$

E.7 Comparative Statics

Prediction 1: *Assuming fixed factor prices and no firing cost, heat shocks reduce labor demand for all firms.*