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Temperature, Labor Reallocation, and Industrial Production: Evidence from India†

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To what degree can labor reallocation mitigate the economic consequences of weather-driven agricultural productivity shocks? I estimate that temperature-driven reductions in the demand for agricultural labor in India are associated with increases in nonagricultural employment. This suggests that the ability of nonagricultural sectors to absorb workers may play a key role in attenuating the economic consequences of agricultural productivity shocks. Exploiting firm-level variation in the propensity to absorb workers, I estimate relative expansions in manufacturing output in more flexible labor markets. Estimates suggest that, in the absence of labor reallocation, local economic losses could be up to 69 percent higher. (*JEL* J23, J43, L60, O13, O14, Q54, Q56)

We know that vagaries in the weather affect agricultural productivity. We know less about how those affected respond, how these responses are influenced by the economic and policy environment, and the degree to which they attenuate economic losses. One potentially important margin of adjustment is the reallocation of workers, either to other sectors of the economy or to unaffected locations. If agricultural workers are able to find other kinds of work, then economic losses can be mitigated. However, if labor market frictions or other market failures impede reallocation, the livelihoods of affected individuals will be inextricably linked to, and at the mercy of, vagaries in the weather. Understanding these issues is crucial

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for developing countries given the significant role of agriculture in the economic lives of the poor.

Combining worker-, firm-, and district-level data with high-resolution meteorological data in India, I explore the empirical relevance of labor reallocation in response to weather-driven changes in agricultural productivity.

I find that increases in temperature are associated with a reduction in agricultural production and, in turn, the employment and wages of agricultural workers. I show that, in India, temperature is a more important driver of agricultural productivity than rainfall, suggesting that previous work, which focuses on rainfall, has been confounded by the omission of temperature. I show that, while the effects of temperature are stable across datasets and specifications, the effects of rainfall are more sensitive.

The effect of weather-driven changes in agricultural productivity on economic opportunities in other sectors is theoretically ambiguous, depending on the degree to which markets are integrated. Reductions in agricultural productivity may reduce local demand, resulting in contractions in other sectors, but they could also result in local changes in comparative advantage, providing opportunities for workers in other tradable sectors and mitigating local demand effects. While temperature is a strong driver of short-run agricultural productivity, I find that it has no effect on agricultural prices following the trade liberalization period in 1991. This suggests that local markets are relatively well integrated, consistent with the findings of Allen and Atkin (2016).

Whether any labor reallocation actually arises depends on the ability of workers to move across sectors and on the ability of other sectors to absorb these workers. I find that, even in the short run, workers are able to move across sectors in response to temperature-driven changes in agriculture productivity. I estimate an offsetting movement of workers into both the manufacturing and services sector. The expansion of employment in services, traditionally thought of as a nontradable sector, suggests that the expansionary benefits of labor reallocation are sufficient to offset reductions in local demand. In addition, I find no detectable changes in the local population through migration. This helps to bound local labor markets and suggests that the empirically relevant margin through which labor reallocation occurs is across sectors within a district rather than across districts. These findings suggest that the ability of nonagricultural sectors to absorb workers within local labor markets is crucial for managing the economic consequences of temperature-driven changes in agricultural productivity.

In light of these results, it is interesting to explore the degree to which labor reallocation mitigates economic losses within each district. I set out to identify the effects of temperature-driven labor reallocation on output, using firm-level data from the formal manufacturing sector. Identifying this effect presents a number of empirical challenges. To interpret the effects of temperature on manufacturing outcomes as being driven by labor reallocation, it is necessary that outcomes not be affected by temperature in any other way. This is a strong assumption. There are potentially many channels through which temperature might affect manufacturing activity. Where empirically relevant channels move in the same direction, we fail to arrive at a meaningful economic interpretation. Where multiple channels are competing, specific effects may be missed or selected interpretations underestimated.

To identify the labor reallocation effects of temperature on manufacturing firms, I exploit variation in the propensity of firms to absorb workers. I construct a firm-level measure of exposure to India's labor regulation environment, building on Besley and Burgess (2004), who classify the rigidity of the labor market using state-level amendments to the Industrial Disputes Act of 1947 (hereafter IDA). The research design exploits differences in the effects of temperature across labor regulation environments. The labor reallocation effect is identified through the differential response of regulated firms to temperature increases in flexible labor markets compared to rigid labor markets. I estimate that there is no differential effect of temperature on unregulated firms that are below the regulatory threshold.

For firms in more flexible labor regulation environments, I estimate that higher temperatures are associated with relative increases in economic activity, consistent with the presence of labor reallocation. For regulated firms in rigid labor markets, I estimate that higher temperatures are associated with contractions in economic activity. This observation is consistent with—but not limited to—existing evidence, suggesting that increases in temperature are associated with reductions in labor productivity and increases in absenteeism (Mackworth 1946, 1947; Hsiang 2010; Cachon, Gallino, and Olivares 2012; Heal and Park 2014; Graff Zivin and Neidell 2014; Somanathan et al. 2015; Adhvaryu, Kala, and Nyshadham 2020). The presence of multiple, competing channels highlights the challenges associated with interpreting the effects of reduced-form temperature estimates. Overall, I estimate a net zero effect on formal manufacturing firms, suggesting that much of the estimated labor reallocation may occur in smaller, informal firms.[1]

Using these estimates, I explore how much larger economic losses would be in the absence of labor reallocation. Back-of-the-envelope calculations suggest that local economic losses could be up to 69 percent larger in the absence of labor reallocation. Collectively, these results suggest that labor reallocation plays an important role in mitigating the economic consequences of temperature increases.

My findings contribute to the literature on how labor markets respond to weather shocks (Paxson 1992; Townsend 1994; Jayachandran 2006; Jessoe, Manning, and Taylor 2018; Kleemans and Magruder 2018; Emerick 2018; Kaur 2019; Santangelo 2019). I document that labor reallocation across sectors is an important margin of adjustment for managing temperature-driven changes in agricultural productivity. Understanding margins of adjustment outside of agriculture is particularly important given the limited evidence of adaptation to higher temperatures within agriculture (Burke and Emerick 2016; Taraz, 2017, 2018). Where existing work has explored the effects of agricultural productivity shocks on other sectors and local economic outcomes, it has largely focused on long-run changes in agricultural productivity arising from permanent changes in technology or the environment (Hornbeck 2012; Hornbeck and Naidu 2014; Hornbeck and Keskin 2015; Bustos, Caprettini, and Ponticelli 2016; Henderson, Storeygard, and Deichmann 2017). Focusing on short-run changes in the weather means that other factors of production, such as capital or the allocation of land, are likely to be held fixed. It provides

[1] Consistent with this conjecture, I estimate meaningful net expansions in output and employment in the informal sector, although point estimates are statistically insignificant.

an opportunity to identify the effects of labor reallocation rather than any collective change in factors of production.

I also highlight the empirical relevance of temperature, as opposed to rainfall, in this context. Much of the literature to date has focused on rainfall and, more often than not, omitted temperature as a control. I document that controlling for temperature significantly dampens the empirical relevance of rainfall on agricultural production and that the effects of rainfall are sensitive to alternative weather data and specifications. By contrast, the effects of temperature are qualitatively and quantitatively robust across datasets and specifications. This is an important distinction because the strategies used to manage the effects of rainfall and temperature shocks are very different.

The empirical relevance of temperature is also important in light of climate change. I contribute to the literature on adaptation to climate change by documenting how higher temperatures affect the manufacturing sector, directly and indirectly, through the movement of labor out of agriculture. The results are encouraging, to the degree that firms and workers are more able to adapt in the long run than in the short run. However, it is important to caveat that the results may not apply in other contexts. The findings suggest that areas with greater market integration, diversification, and worker mobility may be better able to manage economic losses from climate change.

Finally, I contribute to an established literature on the economic consequences of labor market regulations (Oi 1962; Nickell 1978; Besley and Burgess 2004; Ahsan and Pagés 2009; Adhvaryu, Chari, and Sharma 2013; Hsieh and Olken 2014; Chaurey 2015; Bertrand, Hsieh, Tsivanidis 2017; Amirapu and Gechter 2020). I highlight the importance of labor market flexibility for the management of local productivity shocks. I build on the approaches taken by Adhvaryu, Chari, and Sharma (2013) and Chaurey (2015), who exploit state-level variation in the labor regulation environment to explore the differential effects of rainfall shocks. Specifically, I introduce firm-specific exposure to the labor regulation environment, which helps to more precisely identify how the labor regulation environment affects the responsiveness of firms to transitory shocks.

The remainder of the paper is structured as follows: Section I examines the relationship between weather and agricultural production, Section II investigates the degree to which workers are able to move across sectors and space in response to weather-induced labor demand shocks, Section III explores the impact of labor reallocation on manufacturing firms, Section IV discusses the implications of these results and considers how much greater local economic losses could be in the absence of labor reallocation, and Section V concludes.

I. The Effects of Weather on Agricultural Markets

As in many developing countries, agriculture plays an important role in India's economy. During the study period, agriculture accounted for roughly 15–20 percent of GDP, 60–70 percent of land use, and 40–50 percent of employment—mostly landless laborers employed on daily contracts.

A salient feature of India's agricultural landscape is the monsoon (Rosenzweig and Binswanger 1993). The monsoon's arrival in early summer is especially important for the kharif season, which coincides with this period, but also for the rabi season, which begins at the end of the kharif season and continues through the cooler autumn and winter months before harvest in the spring. However, temperature is a consideration often neglected in economic analysis. Temperatures prior to the monsoon affect the onset of the monsoon—it is a thermally driven phenomenon—the degree to which rainfall drains from the soil, and soil temperature, which is important for seed germination and plant growth. High temperatures during the monsoon directly affect the kharif crop and increase the rate of evapotranspiration, which affects the availability of moisture in the soil, necessary for rabi crop production. Finally, high temperatures directly affect the rabi crop, even when irrigation is used.[2] It is important to understand the relative contributions of temperature and rainfall to agricultural production in India, especially given the different strategies required to manage each factor.

In this section, I examine the effects of weather on two sets of agricultural outcomes. First, I examine the degree to which weather affects agricultural production in India, identifying the sign and magnitude of this relationship. Second, I examine the effects of weather on agricultural prices, which indicates the degree to which Indian districts are integrated with other markets—an important factor in determining opportunities for labor reallocation.

A. *Data—Yields and Prices*

Data on crop yields and farm-gate prices come from the ICRISAT Village Dynamics in South Asia Macro-Meso Database (henceforth VDSA), which is compiled from a number of official government data sources. The data analyzed cover 13 major crops across 302 districts in 19 states between 1960 and 2009.[3] I restrict my attention to the period 2001–2007 for comparability with the analysis of local labor markets and industrial production. For each crop and district, the data provide the total area planted, total production in tonnes, and farm-gate prices. I calculate yields as total production divided by total area planted. I also calculate the value of production, defined as price multiplied by yield. Prices, by crop, are deflated to 2001 rupees. Descriptive statistics and further details can be found in online Appendix A.1.

B. *Data—Rainfall and Temperature*

Rainfall and temperature data are collected from the ERA-Interim Reanalysis archive, which provides 6-hourly atmospheric variables for the period on a $0.25° \times 0.25°$ quadrilateral grid. Daily variables are calculated for each district based on an average of all grid points within the district. Although India has a large system of

[2] While temperature is an important determinant of vapor pressure deficit, which irrigation can alleviate, around one-third of the effects of temperature on yield losses arise due to an increase in the pace of crop development, which provides less time for the plant to develop and absorb nutrients and calories (Schlenker and Roberts 2009). Fishman (2012) demonstrates these effects in the context of India by showing that higher temperatures still have a direct effect on rice yields—a crop known to be naturally resistant to higher temperatures—after controlling for irrigation.

[3] The 13 crops are Bajra (Pearl Millet), Barley, Castor seed, Cotton, Finger Millet, Groundnut, Linseed, Maize, Rice, Rape and Mustard Seed, Sorghum, Sugarcane, and Wheat.

weather stations that provide daily readings dating back to the nineteenth century, the spatial and temporal coverage of ground stations that report temperature and rainfall readings has sharply deteriorated over time. Furthermore, there are many missing values in the publicly available series—this is especially problematic when constructing cumulative variables like total rainfall or degree days—a commonly used measure of temperature exposure used in agricultural economics. If we were to base the construction of this data on a selection rule that requires data for 365 days of the year, the database would have very few observations.

By combining observational data with global climate models, reanalysis data provide a consistent best estimate of atmospheric parameters over time and space (Auffhammer et al. 2013). This results in an estimate of the climate system that is more uniform in quality and realism than observations, or any model, could provide alone. This type of dataset is increasingly being used by economists, especially in developing countries, where the quality and quantity of weather data are limited. I also present results using the University of Delaware (UDEL) Rainfall and Temperature dataset, which is commonly used by researchers. Descriptive statistics and further details can be found in online Appendix A.1.

C. *Empirical Specification—Yields and Prices*

The unit of observation in this analysis is a crop within a district. The main empirical specification for estimating the effect of weather on agricultural outcomes is based on the following model,

$$\log Y_{cdt} = f(w_{dt}) + \alpha_{cd} + \alpha_{ct} + \phi_s t + \varepsilon_{cdt},$$

where Y_{cdt} represents yields, the value of production, or farm-gate prices; α_{cd} is a vector of crop $\times$ district fixed effects; and α_{ct} is a vector of crop $\times$ year fixed effects, absorbing all unobserved time-varying differences in the dependent variable that are common across districts. The assumption that shocks and other time-varying factors are common across districts is unlikely to be valid. To address this, I include a set of flexible, state-specific time trends, $\phi_s t$.

The last term is the stochastic error term, ε_{cdt}. I follow Hsiang (2010) by assuming that the error term ε_{dt} is heteroskedastic and serially correlated within a district over time—up to 7 years—(Newey and West 1987) and spatially correlated across contemporaneous districts—up to 1,100 km (Conley 1999).[4]

The term $f(w_{dt})$ is a function of rainfall and temperature. In the most basic specification, $f(w_{dt})$ is modeled as a function of daily average temperature and total rainfall:

$$f(w_{dt}) = \beta_1 \mathit{Temperature}_{dt} + \beta_2 \mathit{Rainfall}_{dt}.$$

[4] Results are robust to using alternative distance choices. Similar inference for temperature is obtained when standard errors are clustered at the state level; however, rainfall estimates are statistically insignificant when clustered at the state level. The inference for rainfall is similar to the inference with Conley standard errors when clustering at the district level; however, standard errors for temperature when clustering is done at the district level are severely underestimated.

As discussed, temperature is important for agricultural production during, and outside, the monsoon period. I therefore use crop calendars to define the relevant time period over which to construct the temperature variables. Alternative specifications, accounting for nonlinearities in the temperature schedule, are presented in online Appendix A.2. Total rainfall is calculated for each state's monsoon period, beginning with the first month in which total monthly rainfall exceeds 100 millimeters (mm) and ending with the first month that rainfall falls below 100 mm. I also explore robustness to alternative measures of rainfall that account for nonlinearities.

D. *Results—Yields and Prices*

Table 1 presents the main results of the agricultural analysis. I estimate that a 1°C increase in temperature is associated with a 12.2 percent reduction in yield (column 1), a 12.3 percent reduction in the value of production (column 2), and no effect on prices (column 3). A 100 mm increase in rainfall is associated with a 1.13 percent increase in yield and a 0.98 percent increase in the value of production and no effect on prices. These results are robust to using nonlinear transformations of temperature (online Appendix Table A2 and Figure A3), to including lag and lead variables for temperature and rainfall (online Appendix Table A3), to using alternative weather datasets (online Appendix Table A5), to using alternative measures of rainfall (online Appendix Table A7), to including the interaction of rainfall and temperature (online Appendix Table A9), and to focusing on the main crop (online Appendix Table A10).

A one standard deviation change in temperature has a larger effect on production (4.15%/SD) than a one standard deviation change in rainfall (2.07%/SD). This highlights the important role that temperature plays in driving agricultural productivity in India. When running the same regressions without temperature, the magnitude of the coefficient for rainfall increases by 65 percent. By contrast, regressing yields on temperature without rainfall increases the coefficient for temperature by only 14 percent (online Appendix Tables A4, A6, and A8). This suggests that the relative importance attributed to rainfall for agricultural production in India may have been overstated in previous work due to the omission of temperature. The discrepancy with past work appears to be more a consequence of the correlation between rainfall and temperature than because the relationship has evolved over time.[5] If anything, the importance of rainfall appears to have increased over time (online Appendix Figure A4).

In online Appendix Figure A5, I show that the relative importance of temperature for agricultural yields holds both before and after the period of trade liberalization in the early 1990s and is largely unaffected by the omission of rainfall. The

[5] The relative importance of temperature does not appear to be a result of the weather data product used. The results are robust to using the University of Delaware Rainfall and Temperature dataset, commonly used by researchers in development economics to examine the effects of rainfall shocks in India and other developing countries (online Appendix Tables A5 and A6). The results are also robust to using an alternative functional form for monsoon rainfall, commonly used in the development economics literature (Jayachandran 2006, Emerick 2018, Kaur 2019). Following Jayachandran (2006), I define a shock to be equal to 1 if rainfall exceeds the eightieth percentile of the rainfall distribution and −1 if rainfall is lower than the twentieth percentile of the district-specific rainfall distribution (online Appendix Tables A7 and A8).

Table 1—The Effects of Weather on Agricultural Outcomes

	log yield (All crops) (1)	log value (All crops) (2)	log price (All crops) (3)
Daily average temperature (°C)	−0.122	−0.123	−0.00158
	(0.0296)	(0.0270)	(0.00949)
Monsoon rainfall (100 mm)	0.0113	0.00980	−0.00149
	(0.00351)	(0.00338)	(0.00171)
Fixed effects	Crop × District and Crop × Year		
Other controls	Linear state-year time trends		
Observations	10,275	10,275	10,275

Notes: Standard errors are adjusted to reflect spatial dependence (up to 1,100 km) as modeled in Conley (1999) and serial correlation (up to a lag of 7 years) as modeled in Newey and West (1987). District distances are computed from district centroids.

relationship between rainfall and yields also appears relatively stable, although it is statistically insignificant during the preliberalization period, when temperature is controlled for. The magnitude of the coefficient on rainfall almost doubles in size when temperature controls are not included (online Appendix Figure A4). I also provide suggestive evidence that the relative importance of temperature might be because higher temperatures are more difficult to manage than low rainfall realizations. Rainfall is storable and can be substituted with groundwater resources (manually or through the use of irrigation systems). The effects of temperature are more difficult to address, requiring heat-resistant crop varieties. I provide suggestive evidence that greater irrigation coverage is able to offset rainfall shortages completely but has little effect in mitigating the effects of higher temperatures (online Appendix Table A11). The returns to irrigation appear substantially smaller when temperature is not included as a control, highlighting the economic and policy relevance of omitted variable bias in this context (online Appendix Table A12). These findings are consistent with existing research suggesting that farmers, both in developed and developing countries, have been limited in their ability to adapt to temperature increases in the short or long run. This suggests that managing the economic consequences of higher temperature within agriculture may be costly (Burke and Emerick 2016; Taraz, 2017, 2018). This highlights the importance of understanding the economic consequences of temperature on other sectors, and the degree to which factor reallocation could mitigate economic losses.

A notable result is that neither rainfall nor temperature has a significant statistical or economic effect on agricultural prices. This suggests that during this time period, Indian districts are reasonably well integrated with other markets. An alternative interpretation is the presence of price support. However, price support has been in existence and remained stable since the 1960s and is thought to benefit only around 6 percent of farmers (Shanta Kumar Committee 2015). By contrast, the effect of temperature on prices has diminished over time as the Indian economy has become more integrated (online Appendix Figure A5). These results are consistent with the findings of Allen and Atkin (2016), who provide direct evidence on the role of economic integration by examining the effect of improvements to market access on agricultural prices in India between 1960 and 2010. They find that increased integration through the expansion of road networks reduced the volatility of local prices to changes in local rainfall.

In light of this evidence, theory predicts that reductions in agricultural production, and the consequent reduction in the demand for agricultural labor, should result in an outflow of workers into other tradable sectors of the economy due to a change in local comparative advantage.[6] Whether this happens in practice is an empirical question and depends on the economic opportunities that agricultural workers have access to. The next section formally tests this hypothesis.

II. The Effects of Weather on Wages and Employment

How do weather-driven changes in agricultural productivity affect labor market outcomes? In this section, I examine the effects of temperature and rainfall on wages, employment, and unemployment within districts.

A. *Data—Wages and Employment*

Data on wages, employment, and unemployment come from the National Sample Survey Organisation (hereafter, the NSS employment survey). The NSS employment survey is a nationally representative household survey that collects information on employment and wages in rural and urban areas. I make use of NSS survey rounds 60, 61, 62, and 64, covering 2003–2004, 2004–2005, 2005–2006, and 2007–2008. I restrict my attention to the sample of districts used in the analysis of agricultural yields, covering both rural and urban areas. The analysis focuses on four sectors, broadly defined as agriculture, manufacturing, services, and construction. I calculate the average day wage and the likelihood of being employed in each sector. The average day wage is defined as the total wage received divided by the number of days worked over the previous seven days. The likelihood of being employed in each of the aggregated sectors in a given district-year is calculated from individual responses to a survey question asking for their sector of engagement or whether they are unemployed at the time of the survey. Results are not sensitive to using responses to a survey question asking for their principal sector of employment. I restrict the sample to include working-aged individuals (those aged 14–65). Results are robust to using the full sample. Descriptive statistics and further details can be found in online Appendix C.1.

Agriculture accounts for an average of 55 percent of the labor force, with manufacturing employing 12.4 percent, services 29.3 percent, and construction 7.8 percent. Unemployment is 3.9 percent of the labor force. Examining the differences in wages across sectors, we observe that the unconditional average day wage of agricultural laborers is significantly lower than the unconditional average day wage in nonagricultural sectors. Whether this unconditional wage gap is driven by selection and human capital differences, adjustment costs, compensating differentials

[6] Online Appendix B presents a simple specific-factors model based on Matsuyama (1992), demonstrating how the labor supply response varies based on market integration.

associated with sector-specific amenities, or bargaining power is unclear. Examining the degree to which workers are able to move across sectors in response to short-run productivity shocks provides insight into whether adjustment costs are likely to be a first-order concern for agricultural workers in this context.

B. *Empirical Specification—Wages and Employment*

The main empirical specification for estimating the effect of weather on local labor market outcomes is based on the following model,

$$Y_{dt} = f(w_{dt}) + \alpha_d + \alpha_t + \phi_s t + \varepsilon_{dt},$$

where Y_{dt} represents the outcome of interest—sectoral labor force shares and the log of average wages; α_d is a vector of district fixed effects, absorbing all unobserved district-specific time-invariant variation in the dependent variables; and α_t is a vector of year fixed effects, absorbing all unobserved time-varying differences in the dependent variable that are common across districts. I also include a set of flexible, state-specific time trends, $\phi_s t$.

Again, $f(w_{dt})$ is a function of rainfall and temperature. In the most basic specification, $f(w_{dt})$ is modeled as a function of daily average temperature measured over the agricultural year and total rainfall measured over the state-specific monsoon period. Results are robust to alternative specifications, accounting for nonlinearities in the temperature schedule, and to accounting for lags and leads (see online Appendix C.2.3).

The last term is the stochastic error term, ε_{dt}. Standard errors are adjusted as in Section IC.

C. *Results—Wages and Employment*

Table 2 presents the effects of temperature and rainfall on the average day wage of workers in each sector within districts. I estimate that an increase in daily average temperature is associated with a reduction in the average day wage of agricultural workers ($-13.4\%/1°\mathrm{C}$), consistent with a reduction in demand for agricultural labor.[7] These results are robust to excluding rainfall as a control (online Appendix Table C3), to accounting for nonlinearities in the temperature distribution (online Appendix Table C14 and Figure C1), and to controlling for lags and leads (online Appendix Table C16). However, the results are sensitive to using the UDEL weather data. The estimated effects are qualitatively similar but more noisily estimated (online Appendix Tables C5 and C6). Across both datasets, I do not estimate any effect of rainfall on the agricultural wage. When temperature is excluded, the estimated effect becomes positive but remains insignificant (online Appendix Table C4). Using the

[7] It is possible that the estimated effect of temperature on agricultural wages could also be a function of supply-side forces, if workers are less willing to work in the heat. In this case, the effect would be biased toward zero. Furthermore, even if supply-side forces are not a meaningful driver of the estimated effect, part of the estimated wage effect could reflect changes in the composition of workers, resulting from the selection of workers out of agriculture biasing a labor demand interpretation.

Table 2—The Effects of Weather on Average Wages

	log agriculture wages (1)	log manufacturing wages (2)	log services wages (3)	log construction wages (4)
Daily average temperature (°C)	−0.134	−0.120	−0.0348	0.0238
	(0.0538)	(0.0676)	(0.0532)	(0.0431)
Monsoon rainfall (100 mm)	−0.00980	−0.0204	0.00403	0.00749
	(0.00501)	(0.0108)	(0.00972)	(0.00723)
Fixed effects	District and year			
Other controls	Linear state-year time trends			
Average wages	52.71	98.39	159.01	79.23
Observations	1,062	1,062	1,062	1,062

Notes: Standard errors are adjusted to reflect spatial dependence (up to 1,100 km) as modeled in Conley (1999) and serial correlation (up to a lag of 7 years) as modeled in Newey and West (1987). District distances are computed from district centroids.

UDEL data, I estimate no effects of rainfall on wages (online Appendix Table C5), although the effect becomes statistically significant when we exclude temperature as a control (online Appendix Table C7). As such, what we can learn about the effects of rainfall on wages in this context is unclear.

In addition to the effects of temperature on agricultural wages, I also estimate reductions in wages for the manufacturing sectors ($-12.0\%/1°\mathrm{C}$). I do not estimate any effects of temperature on the average day wage in the services or construction sectors. In a simple two-sector model of labor reallocation, the movement of workers across sectors should reduce the average wage in destination sectors. We observe this for manufacturing but not for other sectors. This may suggest that there is limited movement into the other sectors. It is also possible that higher temperatures reduce average productivity in the manufacturing sector in addition to the inflow of workers, reducing wages more in this sector.

While reductions in the wage act as an insurance mechanism for farm owners, a reduction in the average wage combined with a reduction in the availability of work—on the intensive or the extensive margin—could have significant welfare effects on agricultural workers. The overall effect depends on whether workers are able to cushion lower wages with work in other sectors. An analysis of wage data alone is not sufficient.[8] It is important to understand the degree to which workers are able to find work in other sectors or locations.

I estimate the effects of temperature and rainfall on employment and unemployment as shares of the labor force, identifying the degree to which workers move across sectors within each district. Table 3 presents the results of this analysis. I estimate that higher temperatures are associated with a significant reduction in the district share of agricultural employment (-7.1 percentage points/1°C), an increase in the district shares of manufacturing (2.04 percentage points/1°C) and services (3.35 percentage points/1°C) employment, no change in the district share

[8] Wage data are likely to be measured with greater error than employment data.

Table 3—The Effects of Weather on the District Labor Force Share of Employment

	Agriculture share (1)	Manufacturing share (2)	Services share (3)	Construction share (4)	Unemployment share (5)
Daily average temperature (°C)	−0.0714	0.0204	0.0335	0.0105	0.00700
	(0.0165)	(0.00867)	(0.00953)	(0.00673)	(0.00370)
Monsoon rainfall (100 mm)	−0.00369	0.00137	0.000943	0.000414	0.000967
	(0.00241)	(0.00115)	(0.00172)	(0.00126)	(0.000507)
Fixed effects	District and year				
Other controls	Linear state-year time trends				
Average share	0.550	0.113	0.220	0.083	0.035
Observations	1,062	1,062	1,062	1,062	1,062

Notes: Standard errors are adjusted to reflect spatial dependence (up to 1,100 km) as modeled in Conley (1999) and serial correlation (up to a lag of 7 years) as modeled in Newey and West (1987). District distances are computed from district centroids.

of construction employment, and a small increase in the district labor force share of unemployment (0.7 percentage points/1°C). This relationship is robust to the exclusion of rainfall as a control (online Appendix Table C8), the use of alternative weather data (online Appendix Tables C10 and C11), using alternative measures of employment (online Appendix Table C13), accounting for nonlinearities in the temperature schedule (online Appendix Table C15 and Figure C2), and controlling for lags and leads of temperature (online Appendix Table C17). As with wages, I estimate no statistically significant, or economically meaningful, effects of rainfall on employment shares across sectors. This result is robust to excluding temperature as a control (online Appendix Table C9) and to using the UDEL weather data (online Appendix Tables C10 and C12). This is consistent with the relative importance of temperature over rainfall for agricultural production in this context discussed in Section IC.

These findings suggest that workers are relatively able to find employment in other sectors of the local economy, following temperature-driven reductions in agricultural productivity. This is consistent with theoretical predictions when markets are well integrated (online Appendix B). As such, the aggregate consequences of temperature-driven changes in agricultural productivity are likely smaller than a sector-specific analysis of the agricultural sector would suggest. Ex ante the overall effect is ambiguous as reductions in agricultural productivity could affect local demand. Ex post we observe reallocations of labor from agriculture to the manufacturing and services sector, suggesting that the labor supply effect attenuates product-demand effects in this context. The absence of an effect in the construction sector, a highly nontradable sector, suggests that temperature-driven local-demand effects are mitigated through labor reallocation.[9] This contrasts with earlier work by Adhvaryu, Chari, and Sharma (2013), who explore the effects of rainfall shocks

[9] I estimate that the difference between the estimated effects for manufacturing and construction is statistically significant, as is the difference between services and construction. This inference is based on the results of statistical tests of equality across models.

on manufacturing in the 1970s, 1980s, and 1990s. They find that rainfall-driven reductions in agricultural productivity are associated with contractions in manufacturing employment, pointing to the relevance of product-demand during India's preliberalization period. As such, while weather-driven product demand shocks were relevant historically, these results suggest that weather-driven product demand shocks may have become relatively less important as markets have become more integrated in India.

In addition to looking at the effects of weather on local economic activity, I also examine the degree to which weather may affect labor market outcomes through migration. The purpose is to examine whether short-run changes in the weather drive reallocations of labor across space, distorting the definition of the local labor market and, consequently, the interpretation of the results. Unlike the substantial movements of labor across sectors within districts, I do not find any evidence that workers are moving across space in response to year-to-year changes in temperature. These results suggest that local labor markets in India can be bounded at the district level. The results of this exercise can be found in online Appendix C.2.5 (Tables C18 and C19).

Collectively, the results presented in this section suggest that workers in India are able to move across sectors within local labor markets in response to transitory labor demand shocks. As such, the aggregate consequences of temperature-driven changes in agricultural productivity are likely smaller than in the absence of labor reallocation. To get a sense of how important labor reallocation is for mitigating economic losses, we need to know how labor reallocation affects economic activity in destination sectors.

III. The Effects of Weather on Manufacturing Plants

What are the consequences of labor reallocation on economic activity in destination sectors? In this section, I set out to identify the effects of temperature-driven labor reallocations on manufacturing production.[10] Identifying this effect is not straightforward. The main challenge is that there are potentially many empirically relevant channels through which temperature could affect manufacturing outcomes. Any estimate of the relationship between temperature and manufacturing outcomes will provide the net effect of all empirically relevant channels. Where empirically relevant channels move in the same direction, we fail to arrive at a meaningful economic interpretation. Where multiple channels are competing, specific effects may be missed or selected interpretations underestimated. In this section, I propose a research design that exploits variation in the propensity of firms to absorb workers in response to transitory changes in labor availability. I seek to identify the empirical relevance of the labor reallocation channel on manufacturing firms and workers separately from any remaining empirically relevant channels.

[10] It is not possible to estimate the effects of temperature on economic activity in the services sector due to data limitations.

A. *Data—Manufacturing Plants*

Data on manufacturing activity come from the Annual Survey of Industries (ASI) collected by the Ministry of Statistics and Program Implementation (MoSPI), Government of India. The ASI covers all registered industrial units that employ 10 or more workers and use electricity or employ at least 20 workers and do not use electricity. The ASI frame is divided into two schedules: the census schedule, which is surveyed every year, and the sample schedule, which is randomly sampled every few years. The ASI has a much wider coverage than other datasets, such as the Census of Manufacturing Industries (CMI) and the Sample Survey of Manufacturing Industries (SSMI), and is comparable to manufacturing surveys in the United States and other industrialized countries. However, the ASI does not cover informal industry, which falls outside the Factories Act of 1948. An important caveat is that the formal manufacturing sector accounts for only 20 percent of manufacturing employment in India, and much of the employment growth in manufacturing since the trade liberalization period of the early 1990s is thought to have occurred in informal tradable industries (Ghani, Kerr, and Segura 2015). As such, it is possible that much of the labor reallocation estimated in Section IIA may arise in the informal manufacturing sector, for which data are far more limited due to the exclusion of informal sector firms from the ASI.[11]

B. *Empirical Strategy*

To identify the empirical relevance of temperature-driven labor reallocation on formal manufacturing plants, I interact year-to-year changes in temperature with variation in India's labor regulation environment—a differences-in-temperature research design. Industrial regulation in India has largely been the result of central planning. However, the area of industrial relations is an exception to this, providing spatial variation in firms' incentives regarding the hiring and firing of workers. The key piece of labor regulation legislation is the Industrial Disputes Act of 1947 (hereafter the IDA). The IDA regulates Indian Labor Law concerning trade unions, setting out conciliation, arbitration, and adjudication procedures to be followed in the case of an industrial dispute, and was designed to offer workers in the formal manufacturing sector protection against exploitation by employers. Up until the mid-1990s, the IDA was extensively amended at the state level, resulting in spatial variation in labor market rigidities.

Following Besley and Burgess (2004), states are coded as either neutral, pro-worker, or pro-employer. A pro-worker amendment is classified as one that decreases a firm's flexibility in the hiring and firing of workers; pro-employer amendments are classified as increasing a firm's flexibility in hiring and firing. West Bengal, Maharashtra, and Odisha are assigned as pro-worker states

[11] In online Appendix D.5, I explore this possibility, using data from the NSS Unorganized Manufacturing Survey. I estimate that higher temperatures are associated with net increases in employment and output. However, the estimates are statistically insignificant at conventional levels. Given the limited availability of data, it is possible that this exercise is underpowered. Furthermore, there is not a research design available to identify the effects of labor reallocation, and so estimates capture the net effect of temperature on informal sector outcomes.

(rigid), Rajasthan, Tamil Nadu, Karnataka, Kerala, and Andhra Pradesh are assigned as pro-employer states (flexible), and the remaining states are assigned as neutral.[12] As there are no changes made to the IDA during the sample period, my measure of the labor regulation environment is time-invariant, capturing spatial variation in the propensity of firms to take advantage of transitory labor supply changes arising from year-to-year changes in agricultural productivity.

The main threat to identification is that state-level variation may simply capture the heterogeneous effects of weather, general equilibrium effects, or other state-level variation, confounding the interpretation of the estimated coefficients. To explore this, I first examine whether there are meaningful differences across the characteristics of firms. In online Appendix Table D1, I do not estimate any meaningful differences in firm characteristics across labor regulation environments either for regulated or unregulated firms. Second, I examine whether temperature has a differential effect on agricultural production between labor regulation environments. I find no evidence in support of this conjecture, indicating that any estimated differences are not driven by differences in the intensity of agricultural productivity shocks (online Appendix Table D2).[13] I also show that weather realizations are uncorrelated with amendments made to the Industrial Dispute Act (online Appendix Table D3). To bolster identification, I combine the spatial variation in the labor regulation environment with firm-level exposure based on Chapter Vb of the IDA, which specifies the size that firms can become before the IDA has a binding effect. The firm size threshold is 50 in West Bengal, 300 in Uttar Pradesh, and 100 elsewhere. There are four groups of firms: Pro-Worker, Regulated; Pro-Worker, Unregulated; Not Pro-Worker, Regulated; Not Pro-Worker, Unregulated. Because unregulated firms are not affected by the IDA, there should be no differential effect of temperature across labor regulation environments for these firms.

Equation (1) presents the empirical specification for this research design:

$$(1) \qquad \log Y_{ijrdst} = \gamma_1 f(w_{dt}) + \gamma_2 f(w_{dt}) \times Flexible_s + \gamma_3 f(w_{dt}) \times Below_r + \gamma_4 f(w_{dt}) \times Below_r \times Flexible_s + \alpha_{jrd} + \alpha_{jrt} + \phi_s t + \varepsilon_{ijrdt}.$$

The unit of analysis is a firm, i, in sector j, in regulatory group r, in district d, in state s at time t. District $\times$ industry fixed effects that are specific to regulated and unregulated firms, α_{jrd}, are included to absorb all unobserved time-invariant variation within these dimensions; industry $\times$ year (α_{jrt}) fixed effects control for sector- and regulatory group–specific time-varying differences that are common across districts; and a set of flexible state-specific time trends ($\phi_s t$) relaxes the assumption

[12] In the original codification of labor market rigidities, Besley and Burgess (2004) code Gujarat as rigid. Following a critique by Bhattacharya (2006) Gujarat is now commonly coded as neutral. I adopt this revision, although in practice it has little effect on the results.

[13] By contrast, I estimate that rainfall has a differential effect on agricultural outcomes across labor regulation environments, suggesting that the intensity of rainfall-driven agricultural productivity shocks differs across labor regulation environments.

that shocks or time-varying omitted variables are common across districts. As in the previous sections, $f(w_{dt})$ is a function of rainfall and temperature. The parameter of interest, γ_2, captures the differential effect of temperature across labor regulation environments for regulated firms. If $\gamma_2 + \gamma_4$ equals zero, there is no differential effect of temperature on unregulated firms, providing support for the identification assumption that there are no other differences correlated with the labor regulation environment that differentially affect the relationship between temperature and firm behavior.

In exploring employment effects, it is important to consider the types of role that movers may work in. If workers move into regulated worker positions, then we would expect there to be a relative increase in employment in more flexible labor regulation environments. There is the possibility, however, that workers may move into what are known as contract worker positions. These are temporary positions. We observe that there are limited wage gaps between workers in agriculture and casual manufacturing workers, suggesting that workers may be more likely to move into these positions (online Appendix Table D5). Contract workers are not de jure regulated under the IDA. It is unclear whether the IDA differentially affects the incentives of firms to hire contract workers in this context. The exemption of contract workers from the IDA may provide a differential incentive to hire contract workers in rigid labor markets, providing an opportunity for firms to bypass hiring restrictions. In this case, we might expect a relative increase in contract workers in rigid labor markets. But contract workers may be de facto regulated by the IDA. The use of contract workers has been vigorously, and in some cases violently, opposed by unions and regulated workers. Unions do not like contract workers as they weaken bargaining power within the firm by diluting union strength. Regulated workers do not like contract workers as they are concerned that they are "taking their jobs." Regulated firms may face significant costs associated with hiring contract workers in response to transitory shocks, especially in rigid labor markets where unions have greater bargaining power. In such a case, there may be differential hiring of contract workers by regulated firms in more flexible labor markets if de facto hiring costs are empirically relevant.[14] Finally, it is important to note that any differential effect is net of any common labor reallocation effect. As such, estimates of the labor reallocation effect may be biased toward zero.

C. *Results—Manufacturing Firms*

Table 4 presents the results of the differences-in-temperature analysis. The coefficient of interest is γ_2, capturing the relative effect of temperature on regulated firms in more flexible labor markets. We observe that regulated firms in more flexible states experience relative expansions in output (10%/1°C) and the employment of contract workers (14.6%/1°C) and a contraction in the average day wage of contract workers (5.8%/1°C). The relative expansion of contract workers in flexible states suggests that de facto hiring costs are empirically relevant in this context. I fail to reject the null hypothesis that there is no relative expansion in the number of regular

[14] In online Appendix D.3, I formalize this reasoning through a simple extension of the model presented in Garicano, Lelarge, and Van Reenen (2016).

TABLE 4—THE DIFFERENTIAL EFFECTS OF TEMPERATURE BY REGULATORY STATUS ON MANUFACTURING FIRMS

	log total output (1)	log workers (contract) (2)	log workers (regular) (3)	log day wage (contract) (4)	log day wage (regular) (5)
Regression estimates					
Daily average temperature (°C): γ_1	−0.129	−0.148	−0.0611	0.00419	−0.0623
	(0.0240)	(0.0479)	(0.0676)	(0.0111)	(0.00818)
Temperature × Flexible: γ_2	0.100	0.146	0.0395	−0.0580	0.0638
	(0.0355)	(0.0614)	(0.0643)	(0.0265)	(0.0225)
Temperature × Below Threshold: γ_3	0.153	0.179	0.101	0.0126	0.0581
	(0.0321)	(0.0978)	(0.0724)	(0.0366)	(0.0147)
Temperature × Flexible × Below Threshold: γ_4	−0.100	−0.270	−0.0840	0.0417	−0.0420
	(0.0408)	(0.120)	(0.0771)	(0.0384)	(0.0270)
Fixed effects	Sector × District × Regulatory Group and Sector × Year × Regulatory Group				
Other controls	Monsoon Rainfall (inc. interactions) and Linear State × Year Time Trends				
Observations	88,846	31,051	88,846	31,051	88,846
Formal tests					
Difference Above Threshold:	0.100	0.145	0.039	−0.058	0.063
H_0: $\gamma_2 = 0$	(0.035)	(0.061)	(0.064)	(0.026)	(0.022)
Difference Below Threshold:	−0.000	−0.124	−0.044	−0.016	0.021
H_0: $\gamma_2 + \gamma_4 = 0$	(0.042)	(0.110)	(0.032)	(0.036)	(0.013)
Group-specific estimates					
{Pro-Worker, Regulated}	−0.129	−0.148	−0.061	0.004	−0.062
H_0: $\gamma_1 = 0$	(0.024)	(0.048)	(0.067)	(0.011)	(0.008)
{Not Pro-Worker, Regulated}	−0.029	−0.002	−0.021	−0.053	0.001
H_0: $\gamma_1 + \gamma_2 = 0$	(0.033)	(0.058)	(0.022)	(0.030)	(0.021)
{Pro-Worker, Unregulated}	0.024	0.031	0.039	0.016	−0.004
H_0: $\gamma_1 + \gamma_3 = 0$	(0.039)	(0.076)	(0.020)	(0.032)	(0.011)
{Not Pro-Worker, Unregulated}	0.024	−0.093	−0.005	0.000	0.017
H_0: $\gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 = 0$	(0.034)	(0.070)	(0.032)	(0.019)	(0.014)

Notes: "Difference Above Threshold" presents the differential effect of temperature on firms above the regulatory threshold in flexible states compared to regulated firms in rigid states. "Difference Below Threshold" presents the differential effect of temperature on unregulated firms below the regulatory threshold in flexible states compared to unregulated firms in rigid states. {Pro-Worker, Regulated} refers to firms in pro-worker states that are above the regulatory threshold. {Not Pro-Worker, Regulated} refers to firms in pro-employer or neutral states that are above the regulatory threshold. {Pro-Worker, Unregulated} refers to firms in pro-worker states that are below the regulatory threshold. {Not Pro-Worker, Unregulated} refers to firms in pro-employer or neutral states that are below the regulatory threshold. District × Sector and Sector × Year fixed effects are regulatory group–specific, meaning that separate fixed effects are included for firms above and below the regulatory threshold. Standard errors are clustered at the state level as this is the level at which the labor regulation policy varies. Results are robust to accounting for broader spatial correlations as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987).

workers. The movement of workers in contract worker positions is consistent with the limited wage gaps between agricultural and casual manufacturing workers. I also estimate a relative increase in the average day wages of regular workers, suggesting that there may be complementarities in the tasks that contract workers and regular workers engage in.[15] Importantly for identification I do not reject the null

[15] In online Appendix D.6.6, I present additional support for this interpretation, finding that regulated firms in more flexible labor markets experience relative increases in productivity (online Appendix Table D16). A speculative interpretation of these findings is that the inflow of relatively low-skilled casual workers frees up permanent workers to engage in more productive tasks, moving firms down the average cost curve. Why firms don't capitalize on this complementarity in cooler years by offering higher wages to contract workers is unclear. One possibility is

hypothesis, H_0: $\gamma_2 + \gamma_4 = 0$. There is no statistically significant differential effect of temperature on unregulated firms. I caveat that the magnitude of the estimate on the contract employment outcome is not precisely zero. The estimate is the opposite sign to the estimated effects for regulated firms in more flexible labor markets, suggesting that estimated differences are not driven by some common, statewide confounding factor—the main threat to identification.

While I estimate a relative expansion in more flexible labor markets, the overall effect of temperature on these regulated firms is zero. The effects of temperature on regulated firms in more rigid labor markets, captured by γ_1, are negative. A 1 degree increase in temperature is associated with a 12.9 percent contraction in output and a 14.8 percent contraction in the employment of contract workers in rigid labor markets. This suggests that in the absence of labor reallocation, higher temperatures would be associated with contractions in manufacturing activity, exacerbating local economic losses. These results are consistent with, though not limited to, an expanding literature suggesting that higher temperatures may have adverse effects on labor productivity and increase absenteeism in nonagricultural sectors (Mackworth 1946, 1947; Hsiang 2010; Cachon, Gallino, and Olivares 2012; Heal and Park 2014; Graff Zivin and Neidell 2014; Somanathan et al. 2015; Adhvaryu, Kala, and Nyshadham 2020). The only group of firms that document net positive, but statistically insignificant, increases in contract worker employment are unregulated firms in more rigid labor markets. The absence of a net increase in employment suggests that the reallocation of workers out of agriculture and into the manufacturing sector described in Section II may be largely captured by smaller firms in the informal sector. In online Appendix Table D6, I provide suggestive evidence that this may be the case, using data from the NSS Unorganized Manufacturing Survey. A 1 degree increase in temperature is associated with a 12 percent increase in the number of informal manufacturing sector workers and a 33 percent increase in output. However, the estimates are not statistically significant at conventional levels. Given limited data availability, it is possible that this exercise is underpowered. Consistent with previous estimates, I estimate no effect of rainfall on informal sector outcomes.

In online Appendix D, I present a series of robustness checks and additional results. First, I show that the main results are robust to alternative codifications of the labor regulation environment (online Appendix Table D7), to using sampling weights (online Appendix Table D8), to controlling for temperature effects that vary by sector and with baseline firm-level characteristics (online Appendix Tables D9–D11), to accounting for nonlinearities in the temperature schedule (online Appendix Table D12 and Figures D1–D5), and to controlling for lags and leads in temperature and rainfall (online Appendix Table D13). In addition, I show that, consistent with the results presented in the previous sections, rainfall does not appear to be empirically relevant in this context (online Appendix Table D14). Results are also robust to using the UDEL weather dataset (online Appendix Table D15). Finally, in light of the observed movement of workers into contract positions, I present

that firms are simply unaware of the returns, as the signal does not rise above other interannual changes in productivity. This information signal is likely to be further distorted by the fact that the productivity increases are relative, due to the direct adverse effects that higher temperatures have on productivity.

results from a secondary research design exploring whether there is a discontinuous change in the effects of temperature at the regulatory threshold. As discussed, contract workers do not count toward the regulatory threshold, and so it is possible for unregulated firms to hire contract workers without becoming regulated. In such a setting, we might expect a greater incentive for unregulated firms in rigid labor markets to hire more workers. By contrast, in more flexible labor markets, this incentive is likely to be smaller. One of the attractive properties of this research design is that it identifies the labor reallocation effect within the same location. Firms above and below the regulatory threshold are affected by the same temperature variation, and so any differential effect is plausibly driven by changes in the regulatory environment. The key identification assumption for this research design is that there are no other factors that change at the regulatory threshold that also differentially affect firm responses to temperature. Note that unlike a standard RDD, it does not necessarily matter if the continuity assumption is violated, e.g., if there is bunching around the regulatory threshold, as long as any other factors that vary at the regulatory threshold do not differentially affect the response of firms to changes in temperature. Further details about the research design can be found in online Appendix D.7.

Online Appendix Table D17 presents the results of this analysis. I estimate that increases in temperature are associated with a discontinuous relative increase in output (3%/1°C) and the employment of contract workers (13.5%/1°C) just below the regulatory threshold—unregulated firms that are not subject to the IDA experience relative expansion in rigid labor markets. There are no discontinuous effects of temperature at the regulatory threshold in more flexible labor markets. Online Appendix Tables D18–D24 present additional results and robustness tests.

Collectively, the results presented in this section suggest that temperature increases are associated with relative expansions in the formal manufacturing sector, offsetting the direct costs associated with temperature (Mackworth 1946, 1947; Hsiang 2010; Cachon, Gallino, and Olivares 2012; Heal and Park 2014; Graff Zivin and Neidell 2014; Somonathan et al. 2015; Adhvaryu, Kala, and Nyshadham 2020). Using these estimates, the following section engages in a simple thought experiment to explore how much more costly the local economic losses associated with temperature increases might be in the absence of labor reallocation.

IV. Back-of-the-Envelope Calculations

In this section, I explore what the results discussed so far imply for local economic losses within each district. I consider the potential impact of shutting down labor reallocation across sectors by increasing the rigidity of the labor market across India to the level of pro-worker states. The purpose of this thought experiment is to explore how much worse the local economic consequences of temperature increases could be in the absence of labor reallocation.

Table 5 shows that a 1°C increase in temperature is associated with a reduction in agricultural GDP (−11.2%/1°C), a reduction in total manufacturing GDP (−2.56%/1°C), and no change in services or construction GDP. Overall, a 1°C increase in temperature is associated with a 2.58% reduction in total GDP. These

Table 5—The Effects of Temperature on GDP

	log GDP (total) (1)	log GDP (agriculture) (2)	log GDP (manufacturing) (3)	log GDP (services) (4)	log GDP (construction) (5)
Daily average temperature °C	−0.0259	−0.112	−0.0257	−0.0113	0.0161
	(0.0114)	(0.0446)	(0.0132)	(0.00881)	(0.0194)
Fixed effects	District and year				
Other controls	Rainfall and linear state-year time trends				
Observations	3,468	3,468	3,468	3,468	3,468

Notes: All dependent variables are in logs. Standard errors are adjusted to reflect spatial dependence (up to 1,100 km) as modeled in Conley (1999) and serial correlation (up to a lag of 7 years) as modeled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the state level.

Table 6—Back-of-the-Envelope Calculations

	Baseline (1)	Shutting down labor reallocation (2)	(3)	(4)
Informal (20 percent)	5.4%	5.4%	5.4%	−12.9%
Unregulated formal (13.5 percent)	2.5%	2.5%	−12.9%	−12.9%
Regulated formal (66.5 percent)	−6%	−12.9%	−12.9%	−12.9%
Total manufacturing effect	−2.57%	−7.16%	−9.24%	−12.9%
Total effect (aggregate)	−2.59%	−3.58%	−3.87%	−4.39%
Change (percent)	–	38%	49%	69%

Notes: Column 1 (Baseline) provides a decomposition of the effect of a 1°C increase in temperature on manufacturing GDP decomposed into the regulated and unregulated formal manufacturing sector, using the estimated effects of a 1°C increase in temperature on firm-level output, and the informal sector, whereby the informal sector effect is imputed as the residual effect of a 1°C increase in temperature required to produce the estimated effect on manufacturing GDP. The decomposition of output between the informal sector is based on the assumption that 80 percent of output is produced in the formal sector. This 80 percent is divided into the regulated (66.5 percent) and unregulated (13.5 percent) formal sector, calculated as the share of total output in firms above and below the regulatory thresholds. Columns 2, 3, and 4 consider the effects of increasing the rigidity of the labor market for all states. Column 2 increases rigidity within the regulated formal manufacturing sector. Column 3 increases the rigidity for both the regulated and unregulated formal manufacturing sector. Column 4 increases the rigidity for all firms, including those in the informal sector.

estimates form the baseline for the thought experiment and are reported in column 1 of Table 6.

I split total manufacturing GDP into three components: the informal manufacturing sector (20 percent of manufacturing GDP), the regulated formal manufacturing sector (66.5 percent), and the unregulated formal manufacturing sector (13.5 percent).[16] Next, I estimate the average effect of temperature on the total output of

[16] For convenience, the shares are assumed to be constant across states. I assume that 80 percent of output is from the formal sector and then calculate the share of output for regulated and unregulated firms within the formal sector, using the share of total output above and below the regulatory threshold.

regulated and unregulated firms. On average, a 1°C increase in temperature is associated with a 6 percent reduction in the output of regulated firms. On average, a 1°C increase in temperature is associated with a 2.5 percent increase in output for unregulated firms. The residual effect of temperature on the informal sector, necessary to induce a 2.57 percent reduction in total manufacturing GDP, is 5.4 percent increase.[17] The positive imputed effects of temperature on the informal manufacturing sector are consistent with the estimated expansionary net effect of temperature on the number of informal sector workers, presented in online Appendix Table D6.

In columns 2, 3, and 4 of Table 6, I consider the impact of increasing the rigidity of all labor markets in India to the level of pro-worker states. The purpose of this exercise is to understand how much larger the local economic damages from temperature increases would be in the absence of labor reallocation. First, I consider the effects of increasing rigidity only in the regulated formal sector. I do this by inducing a 12.9 percent reduction in output for all firms, equivalent to the estimated effects of temperature in rigid labor markets. For simplicity, I assume that workers are not able to find employment in other sectors and instead become unemployed. Under these assumptions, a 1°C increase in temperature would be associated with a 6.47 percent reduction in local manufacturing GDP and a 3.49 percent reduction in total GDP, corresponding to a 38 percent increase in local economic damages. Second, I consider the effects of increasing the rigidity of the labor market in the unregulated formal sector, equivalent to increasing the scope of the Industrial Disputes Act to unregulated firms, to the level of pro-worker states. Again, I assume that these workers are left unemployed. In this case, a 1°C increase in temperature is associated with a 9.13 percent reduction in manufacturing GDP and a 3.86 percent reduction in total GDP, corresponding to a 49 percent increase in local economic damages. Finally, I consider the effects of restricting movement into the informal manufacturing sector. As above, I assume that these workers are left unemployed. In this case, a 1°C increase in temperature is associated with a 12.9 percent reduction in manufacturing GDP and a 4.39 percent reduction in total GDP, corresponding to a 69 percent increase in local economic damages. These simple back-of-the-envelope calculations highlight the important role labor reallocation currently plays in mitigating the economic consequences of temperature increases.

I note caveats. It is unclear whether these estimates represent upper or lower bounds. The calculations do not account for behavioral responses or general equilibrium effects that might arise as a consequence of restricted labor reallocation. Affected workers may engage in alternative strategies to mitigate the economic effects of temperature-driven reductions in the demand for agricultural labor. To the degree that such adjustments are empirically relevant, the calculations may represent an upper bound. But reductions in income may induce reductions in local demand if there are limited outside options, negatively affecting other sectors. In this case, the calculations may represent a lower bound.

[17] $(-6\% \times 0.665) + (2.5 \times 0.135) + (5.4 \times 0.2) = -2.57\%$.

V. Conclusion

This paper highlights the important role that labor reallocation can play in managing the economic consequences of temperature-driven changes in agricultural productivity. I find that workers are relatively able to move across sectors, that these workers move into casual positions, and that this reallocation is associated with significant expansions in manufacturing output. This finding suggests that the ability of other sectors to absorb workers may play an important role in managing the economic consequences of temperature-driven changes in agricultural productivity. However, the benefits of labor reallocation are attenuated by direct adverse effects of temperature on manufacturing activity. Back-of-the-envelope calculations suggest that total economic losses could be up to 69 percent larger, highlighting the importance of labor mobility in attenuating the economic consequences of sectoral productivity shocks. The increased losses arise largely from the direct adverse effects of temperature on manufacturing firms. As such, future research should seek to understand the costs, and constraints, associated with managing the adverse effects of temperature.

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