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ABSTRACT

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

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 non-agricultural employment. This suggests that the ability of non-agricultural 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% higher.

JEL Classification: Q56, O13, J21, F16

Keywords: temperature, labor reallocation, industrial production

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1 Introduction

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 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 data sets 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 non-tradable 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 non-agricultural 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 et al., 2012, Heal and Park, 2014, Graff Zivin and Neidell, 2014, Sudarshan et al., 2015, Adhvaryu et al., 2019). 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% 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 et al., 2018, Magruder and Kleemans, 2018, Emerick, 2018, Magruder and Kleemans, 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, Henderson et al., 2017, Hornbeck and Keskin, 2015, Bustos et al., 2016). 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 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 data sets 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

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

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 et al., 2013, Hsieh and Olken, 2014, Chaurey, 2015, Bertrand et al., 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 et al. (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 2 examines the relationship between weather and agricultural production; Section 3 investigates the degree to which workers are able to move across sectors and space in response to weather-induced labor demand shocks; Section 4 explores the impact of labor reallocation on manufacturing firms; Section 5 discusses the implications of these results and considers how much greater local economic losses could be in the absence of labor reallocation; Section 6 concludes.

2 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% of GDP, 60–70% of land use, and 40–50% 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.

2.1 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 Appendix A.1.

2.2 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 weather stations that provide daily readings dating back to the 19th 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

[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).

[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.

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 provides 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 is limited. I also present results using the University of Delaware Rainfall and Temperature dataset, which is commonly used by researchers. Descriptive statistics and further details can be found in Appendix A.1.

2.3 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 1,100km – (Conley, 1999).[4]

$f(w_{dt})$ 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:

[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.

$$f(w_{dt}) = \beta_1 Temperature_{dt} + \beta_2 Rainfall_{dt}$$

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 non-linearities in the temperature schedule, are presented in Appendix A.2. Total rainfall is calculated for each state's monsoon period, beginning with the first month in which total monthly rainfall exceeds 100mm and ending with the first month that rainfall falls below 100mm. I also explore robustness to alternative measures of rainfall that account for non-linearities.

2.4 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% reduction in yield (column 1), a 12.3% reduction in the value of production (column 2), and no effect on prices (column 3). A 100mm increase in rainfall is associated with a 1.13% increase in yield and a 0.98% increase in the value of production, and no effect on prices. These results are robust to: using non-linear transformations of temperature (Table A2 and Figure A3); to including lag and lead variables for temperature and rainfall (Table A3); to using alternative weather data sets (Table A5); using alternative measures of rainfall (Table A7); including the interaction of rainfall and temperature (Table A9); focusing on the main crop (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%. By contrast, regressing yields on temperature without rainfall increases the coefficient for temperature by only 14% (Table 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

[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 (Table 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,

appears to have increased over time (Figure A4).

In 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 relationship between rainfall and yields also appears relatively stable, although it is statistically insignificant during the pre-liberalization period, when temperature is controlled for. The magnitude of the coefficient on rainfall almost doubles in size when temperature controls are not included (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 ground water 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 (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 (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 or temperature have 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% 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 (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

2018, Kaur, 2019). Following Jayachandran (2006) I define a shock is defined to be equal to 1 if rainfall exceeds the 80th percentile of the rainfall distribution and -1 if rainfall is lower than the 20th percentile of the district-specific rainfall distribution (Table A7 and A8).

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.

3 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.

3.1 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 which collects information on employment and wages in rural and urban areas. I make use of NSS survey rounds 60, 61, 62 and 64, covering 2003–04, 2004–05, 2005–06, and 2007–08. I restrict my attention to the sample of districts used in the analysis of agricultural yields, covering both rural and urban areas. The analysis focusses 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 Appendix C.1.

Agriculture accounts for an average of 55% of the labor force, with manufacturing employing 12.4%, services 29.3%, and construction 7.8%. Unemployment is 3.9% of the labor force.

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

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 non-agricultural sectors. Whether this unconditional wage gap is driven by selection and human capital differences, adjustment costs, compensating differentials 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.

3.2 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 non-linearities in the temperature schedule, and to accounting for lags and leads (see Appendix C.2.3).

The last term is the stochastic error term, ε_{dt}. Standard errors are adjusted as in Section 2.3.

3.3 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°C), consistent with a reduction in demand for agricultural labor.[7] These results are robust to:

[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 towards zero. Furthermore, even if supply-side forces are not a meaningful driver of the estimated effect,

excluding rainfall as a control (Table C3); to accounting for non-linearities in the temperature distribution (Table C14 and Figure C1); and to controlling for lags and leads (Table C16). However, the results are sensitive to using the UDEL weather data. The estimated effects are qualitatively similar but more noisily estimated (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 (Table C4). Using the UDEL data I estimate no effects of rainfall on wages (Table C5), although the effect becomes statistically significant when we exclude temperature as a control (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°C). I do not estimate any effects of temperature on the average day wage in the services or construction sector. 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 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 (Table C8); the use of alternative weather data (Tables C10 and C11); using alternative measures of employment (Table C13); accounting

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.

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

for non-linearities in the temperature schedule (Table C15 and Figure C2); controlling for lags and leads of temperature (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 (Table C9) and to using the UDEL weather data (Tables C10 and C12). This is consistent with the relative importance of temperature over rainfall for agricultural productivion in this context discussed in Section 2.3.

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 (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 non-tradable sector, suggests that temperature-driven local-demand effects are mitigated through labor reallocation.[9] This contrasts with earlier work by Adhvaryu et al. (2013), who explore the effects of rainfall shocks on manufacturing in the 1970s, 80s and 90s. 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 pre-liberalization 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 Appendix C.2.5 (Tables C18 and C19).

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

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.

4 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 straight forward. 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.

4.1 Data – Manufacturing Plants

Data on manufacturing activity comes 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

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

cover informal industry, which falls outside the Factories Act of 1948. An important caveat is that the formal manufacturing sector accounts for only 20% 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 et al., 2015). As such, it is possible that much of the labor reallocation estimated in section 3.1 may arise in the informal manufacturing sector, for which data is far more limited due to the exclusion of informal sector firms from the ASI.[11]

4.2 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 (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

[11]In 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 is only able to provide an estimate of the net effect of temperature on informal sector outcomes.

[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.

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 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 (Table D2).[13] I also show that weather realizations are uncorrelated with amendments made to the Industrial Dispute Act (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; Non Pro-Worker, Regulated; Non 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,

$$\begin{aligned}\log Y_{ijrdst} \quad = \quad & \gamma_1 f(w_{dt}) + \gamma_2 f(w_{dt}) \times \textsc{Flexible}_s \\ & +\gamma_3 f(w_{dt}) \times \textsc{Below}_r + \; \gamma_4 f(w_{dt}) \times \textsc{Below}_r \times \textsc{Flexible}_s \\ & +\alpha_{jrd} + \alpha_{jrt} + \phi_s t + \varepsilon_{ijrdt}. \end{aligned} \tag{1}$$

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 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

[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.

across labor regulation environments for regulated firms. If $\gamma_2 + \gamma_4$ equal zero there is no differential effect of temperature on unregulated firms, providing support for the identification assumption that there are no other differences correlated 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 causal manufacturing workers, suggesting that workers may be more likely to move into these positions (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 towards zero.

4.3 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 expan-

[14] In Appendix D.3 I formalize this reasoning through a simple extension of the model presented in Garicano et al. (2016).

sion 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 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 worker and regular workers engage in.[15] Importantly for identification I do not reject the null 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, state-wide 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 one degree increase in temperature is associated with a 12.9% contraction in output and a 14.8% 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 non-agricultural sectors (Mackworth, 1946, 1947, Hsiang, 2010, Cachon et al., 2012, Heal and Park, 2014, Graff Zivin and Neidell, 2014, Sudarshan et al., 2015, Adhvaryu et al., 2019). 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 3 may be largely captured by smaller firms in the informal sector. In Table D6 I provide suggestive evidence that this may be the case, using data from the NSS Unorganized Manufacturing Survey. A one degree increase

[15] In 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 (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 that firms are simply unaware of the returns, as the signal does not rise above other inter-annual 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.

in temperature is associated with a 12% increase in the number of informal manufacturing sector workers and a 33% 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 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 (Tables D7), to using sampling weights (Table D8), to controlling for temperature effects that vary by sector and with baseline firm-level characteristics (Table D9-D11), to accounting for non-linearities in the temperature schedule (Table D12 and Figures D1 - D5), and to controlling for lags and leads in temperature and rainfall (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 (Table D14). Results are also robust to using the UDEL weather data set (Table D15). Finally, in light of the observed movement of workers into contract positions I present 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 towards 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 effect the response of firms to changes in temperature. Further details about the research design can be found in Appendix D.7.

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. 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 et al., 2012, Heal and Park, 2014, Graff Zivin and Neidell, 2014, Sudarshan et al., 2015, Adhvaryu et al., 2019). 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.

5 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 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% of manufacturing GDP), the regulated formal manufacturing sector (66.5%) and the unregulated formal manufacturing sector (13.5%).[16] Next I estimate the average effect of temperature on the total output of regulated and unregulated firms. On average, a 1°C increase in temperature is associated with a 6% reduction in the output of regulated firms. On average, a 1°C increase in temperature is associated with a 2.5% increase in output for unregulated firms. The residual effect of temperature on the informal sector, necessary to induce a 2.57% reduction in total manufacturing GDP, is 5.4% 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 Table D6.

I split total manufacturing GDP into three components: the informal manufacturing

[16] For convenience, the shares are assumed to be constant across states. I assume that 80% 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.

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

sector (20% of manufacturing GDP), the regulated formal manufacturing sector (66.5%) and the unregulated formal manufacturing sector (13.5%).[18] Next I estimate the average effect of temperature on the total output of regulated and unregulated firms. On average, a 1°C increase in temperature is associated with a 6% reduction in the output of regulated firms. On average, a 1°C increase in temperature is associated with a 2.5% increase in output for unregulated firms. The residual effect of temperature on the informal sector, necessary to induce a 2.57% reduction in total manufacturing GDP, is 5.4% increase.[19] 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 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% 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% reduction in local manufacturing GDP and a 3.49% reduction in total GDP, corresponding to a 38% 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% reduction in manufacturing GDP and a 3.86% reduction in total GDP, corresponding to a 49% 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% reduction in manufacturing GDP and a 4.39% reduction in total GDP, corresponding to a 69% 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.

[18] For convenience, the shares are assumed to be constant across states. I assume that 80% 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.

[19] $(-6\% \times 0.665) + (2.5 \times 0.135) + (5.4 \times 0.2) = -2.57\%$.

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.

6 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% 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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Tables and Figures

Table 1: The Effects of Weather on Agricultural Outcomes

	(1) log Yield (All Crops)	(2) log Value (All Crops)	(3) log Price (All Crops)
Daily Average Temperature (°C)	-0.122***	-0.123***	-0.00158
	(0.0296)	(0.0270)	(0.00949)
Monsoon Rainfall	0.0113***	0.00980***	-0.00149
(100mm)	(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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) 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.

Table 2: The Effects of Weather on Average Wages

	(1) log Agriculture Wages	(2) log Manufacturing Wages	(3) log Services Wages	(4) log Construction Wages
Daily Average Temperature (°C)	-0.134** (0.0538)	-0.120* (0.0676)	-0.0348 (0.0532)	0.0238 (0.0431)
Monsoon Rainfall (100mm)	-0.00980* (0.00501)	-0.0204* (0.0108)	0.00403 (0.00972)	0.00749 (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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) 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.

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

	(1) Agriculture Share	(2) Manufacturing Share	(3) Services Share	(4) Construction Share	(5) Unemployment Share
Daily Average Temperature (°C)	-0.0714*** (0.0165)	0.0204** (0.00867)	0.0335*** (0.00953)	0.0105 (0.00673)	0.00700* (0.00370)
Monsoon Rainfall (100mm)	-0.00369 (0.00241)	0.00137 (0.00115)	0.000943 (0.00172)	0.000414 (0.00126)	0.000967* (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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) 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.

Table 4: The Differential Effects of Temperature by Regulatory Status on Manufacturing Firms

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
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 $\times$ Flexible: γ_2	0.100**	0.146**	0.0395	-0.0580**	0.0638**
	(0.0355)	(0.0614)	(0.0643)	(0.0265)	(0.0225)
Temperature $\times$ 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 $\times$ Flexible $\times$ 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 $\times$ District $\times$ Regulatory Group & Sector $\times$ Year $\times$ Regulatory Group				
Other Controls	Monsoon Rainfall (inc. interactions) & Linear State $\times$ Year Time Trends				
Observations	88,846	31,051	88,846	31,051	88,846
Formal Tests					
Difference Above Threshold: $H_0 : \gamma_2 = 0$	0.100**	0.145**	0.039	-0.058**	0.063**
	(0.035)	(0.061)	(0.064)	(0.026)	(0.022)
Difference Below Threshold: $H_0 : \gamma_2 + \gamma_4 = 0$	-0.000	-0.124	-0.044	-0.016	0.021
	(0.042)	(0.110)	(0.032)	(0.036)	(0.013)
Group-Specific Estimates					
{Pro-Worker, Regulated} $H_0 : \gamma_1 = 0$	-0.129***	-0.148***	-0.061	0.004	-0.062***
	(0.024)	(0.048)	(0.067)	(0.011)	(0.008)
{Not Pro-Worker, Regulated} $H_0 : \gamma_1 + \gamma_2 = 0$	-0.029	-0.002	-0.021	-0.053*	0.001
	(0.033)	(0.058)	(0.022)	(0.030)	(0.021)
{Pro-Worker, Unregulated} $H_0 : \gamma_1 + \gamma_3 = 0$	0.024	0.031	0.039	0.016	-0.004
	(0.039)	(0.076)	(0.020)	(0.032)	(0.011)
{Not Pro-Worker, Unregulated} $H_0 : \gamma_1 + \gamma_2 + \gamma_3 + \gamma_4 = 0$	0.024	-0.093	-0.005	0.000	0.017
	(0.034)	(0.070)	(0.032)	(0.019)	(0.014)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. "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 $\times$ Sector and Sector $\times$ 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).

Table 5: The Effects of Temperature on GDP

	(1) log GDP (Total)	(2) log GDP (Agriculture)	(3) log GDP (Manufacturing)	(4) log GDP (Services)	(5) log GDP (Construction)
Daily Average Temperature °C	-0.0259** (0.0114)	-0.112** (0.0446)	-0.0257* (0.0132)	-0.0113 (0.00881)	0.0161 (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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. All dependent variables are in logs. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) 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	Shutting Down Labor Reallocation		
	(1)	(2)	(3)	(4)
Informal (20%)	5.4%	5.4%	5.4%	-12.9%
Unregulated Formal (13.5%)	2.5%	2.5%	-12.9%	-12.9%
Regulated Formal (66.5%)	-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 (%)	–	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% of output is produced in the formal sector. This 80% is divided into the regulated (66.5%) and unregulated (13.5%) 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.

Online Appendices – Not for Publication

Contents

A The Effects of Weather on Agricultural Markets: Supporting Evidence

In this appendix I provide more detail on the data used for the analysis of weather on agricultural markets in India, as well as supporting evidence and additional results.

A.1 Agricultural Data

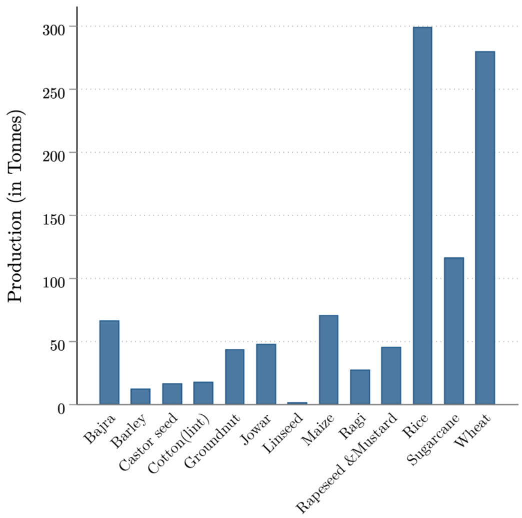
As discussed in the main paper, the data is collected from the ICRISAT Village Dynamics in South Asia Macro-Meso Database (henceforth VDSA), which is compiled from a number of official government datasources. Descriptive statistics for the agricultural data analysis are found in Table A1.

Table A1: Descriptive Statistics - Agriculture Markets in India (2001–2007)

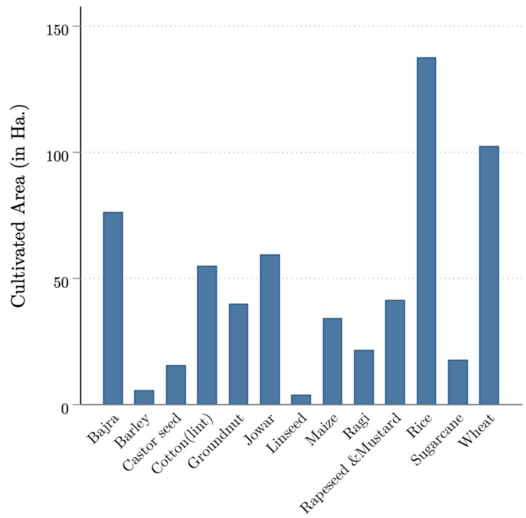
	Mean	Std. Dev. (within)	Std. Dev. (between)	Observations
Panel A: Agricultural Data				
Yield	1.762	0.468	1.673	10,275
Value (Rs.)	19,186.89	10,505.44	22,324.76	10,275
Production ('000 Tonnes)	110.462	48.954	248.789	10,275
Area ('000 Hectares)	58.210	14.794	99.884	10,275
Price (Rs./Tonne)	12,153.88	4,083.989	7492.096	10,275
Crops	7.812	0	3.805	10,275
Average Crop Share	0.151	0.0268	0.215	10,275
Average Share of Main Crop	0.563	0.041	0.182	10,275
Panel B: Meteorological Data				
Daily Average Temperature (°C)	25.359	0.343	4.820	10,275
Degree Days ($t_L = 17, t_H = \infty$)	1,005.928	63.142	644.298	10,275
Degree Days ($t_L = 0, t_H = 17$)	5,261.183	29.944	1,890.894	10,275
Monsoon Rainfall (100 mm)	8.25	1.849	4.29	10,275
Monsoon Rainfall Shock (-1/0/1)	0.132	0.525	0.331	10,275

Figure A1 provides summary statistics for the 13 crops used. We observe from the figures that both rice and wheat are the most produced crops in terms of cultivated land area and total production and that they also comprise the largest share of production and cultivated land area within district (Figure A2). In terms of yields, sugarcane is show to have one of the highest yields (Figure A1c).

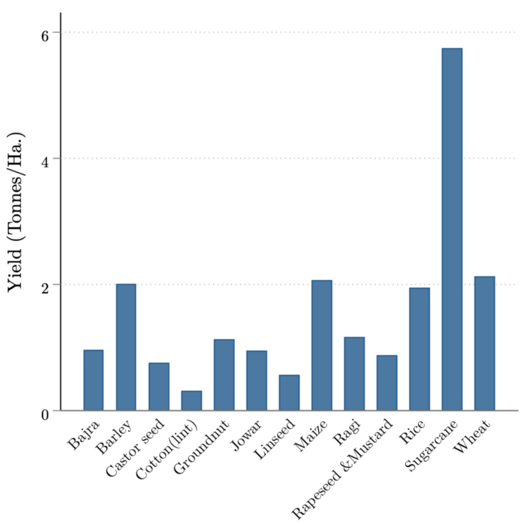
Figure A1: Agricultural Production, Cultivated Area, Yields and Prices by Crop



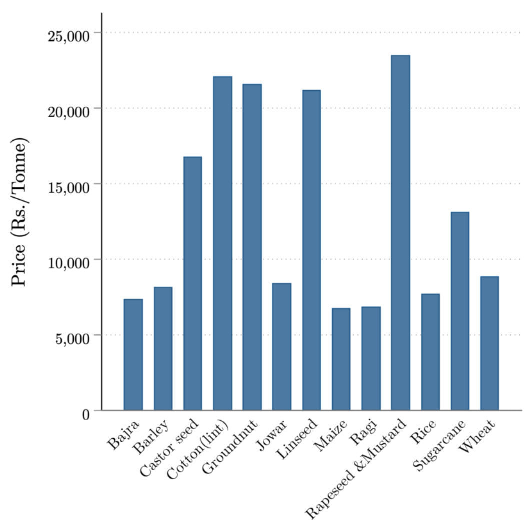
(a) Production ('000 tonnes)



(b) Cultivated Area ('000 Ha.)

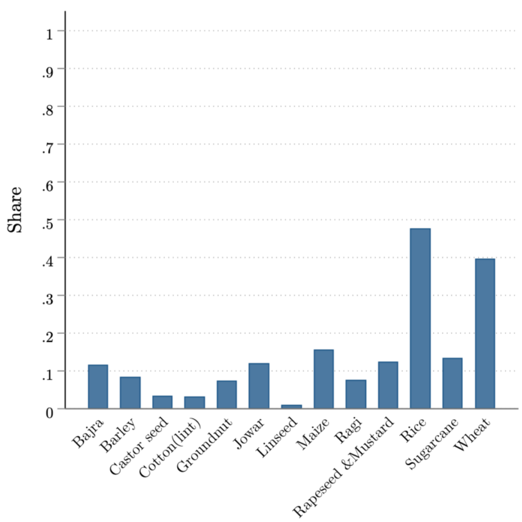


(c) Yield

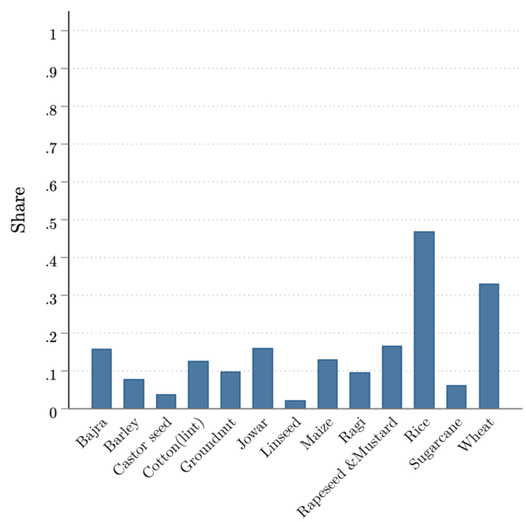


(d) Price (2001 Rs./Tonne)

Figure A2: District Shares of Agricultural Production and Cultivated Area by Crop



(a) District Share of Cultivated Area



(b) District Share of Cultivated Area

A.2 Non-Linearities in the Temperature Schedule

In this section I explore the degree to which there are non-linearities in the temperature schedule. A large literature in agricultural science has demonstrated that the relationship between agricultural yields and weather is highly nonlinear (Schlenker and Roberts, 2009; Auffhammer and Schlenker, 2014). To account for the relevance of any non-linearities, I engage in two exercises. First, I apply the concept of growing degree days, which measure the amount of time a crop is exposed between a given lower and upper bound, with daily exposures summed over the season. Denoting the lower bound as t_l, the upper bound as t_h, and t_d as the daily average temperature on a given day,

$$GDD_{d;t_l;t_h} = \begin{cases} 0 \text{ if } t_d \leq t_l \\ t_d - t_l \text{ if } t_l < t_d < t_h \\ t_h - t_l \text{ if } t_h \leq t_d \end{cases} \tag{2}$$

These daily measures are then summed over the period of interest.[20] This approach is appealing for several reasons. First, the existing literature suggests that this simple function delivers results that are very similar to those estimated using more complicated functional forms (Schlenker and Roberts, 2009; Burgess et al. 2016; Burke and Emerick, 2016). Secondly, these other functional forms typically feature higher order terms, which in a panel setting means that the unit-specific mean re-enters the estimation, as is the case with using the quadratic functions (McIntosh and Schlenker, 2006). This raises omitted variable concerns, since identification in the panel models is no longer limited to location-specific variation over time.

Using the notion of GDD, I model weather as a simple piecewise linear function of temperature and precipitation,

$$f(w_{dt}) = \beta_1 GDD_{dt;t_l;t_h} + \beta_2 GDD_{dt;t_h;\infty} + \beta_3 Rain_{dt} \tag{3}$$

The lower temperature "piece" is the sum of GDD between the lower bound $t_l = 0$ and kink-point t_h. The upper temperature "piece" has a lower bound of t_h and is unbounded above. The kink-point in the distribution t_h is determined by estimating an agricultural

[20] For example, if we set t_l equal to 0°C and t_h equal to 24°C, then a given set of observations $\{-1, 0, 8, 12, 27, 30, 33\}$, would provide $GDD_{dt;0;24} = \{0, 0, 8, 12, 24, 24\}$. Similarly, if we wanted to construct a piecewise linear function setting t_l equal to 24 and t_h equal to infinity, the second "piece" would provide $CDD_{dt;24;\infty} = \{0, 0, 0, 0, 6, 9\}$. These values are then summed over the period of interest, in this case $CDD_{dt;0;24} = 68$ and $CDD_{dt;24;\infty} = 15$. This approach accounts for any differences in the response to this temperature schedule relative to a different schedule with the same daily average temperature.

production function, looping over all possible thresholds and selecting the model with the lowest root-mean-square error. This results in a kink-point at 23°C. This kink-point is applied to all results for consistency.

The second approach explores the effects of non-linearities in the temperature schedule and captures the distribution of daily temperatures in district d within year t, by counting the number of days that the daily average temperature fell within the jth bin of 10 temperature bins. I estimate separate coefficients for each of the temperature bin regressors, using the modal bin as a reference category to minimize multicollinearity concerns. So as to retain power, I restrict the lowest bin to contain all days that are < 15°C and the highest bin to contain all days that are > 31°C. Each of the bins are 2°C wide. Using this approach, I model weather as a flexible function of temperature and precipitation,

$$f(w_{dt}) = \sum_{j=1}^{10} \beta_j Temp_{dtj} + \beta_3 Rain_{dt} \tag{4}$$

This approach makes a number of assumptions about the effects of daily temperatures on the outcomes explored, as discussed in Burgess et al. (2016). First, the approach assumes that the impact of daily temperature is determined by the daily mean alone, rather than intra-day variations in temperature. Second, the approach assumes that the impact of a day's average temperature on the outcome of interest is constant within each 2°C interval. Finally, by using the total number of days in each bin in each year, it is assumed that the sequence of relatively hot and cold days is irrelevant for how hot days affect the annual outcomes.

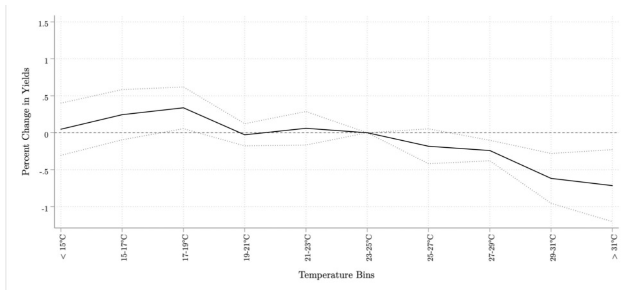
The results of these exercises are presented below for each group of outcome variables.

Table A2: Degree Days and Agricultural Outcomes

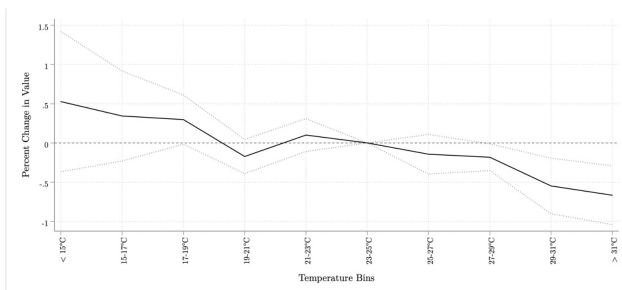
	(1) Log Value (All Crops)	(2) Log Yield (All Crops)	(3) Log Price (All Crops)
Degree Days (10 days)	-0.00800***	-0.00777***	0.000227
$t_L = 23, t_H = \infty$	(0.00207)	(0.00182)	(0.000614)
Degree Days (10 days)	-0.000871	-0.00354*	-0.00267
$t_L = 0, t_H = 23$	(0.00153)	(0.00213)	(0.00166)
Rainfall Controls	Yes	Yes	Yes
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	10,275	10,275	10,275

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) as modeled in Conley (1999) and serial correlation (up to 7-years) as modeled in Newey and West (1987). District distances are computed from district centroids. Results are also robust to using cluster robust standard errors at the state level.

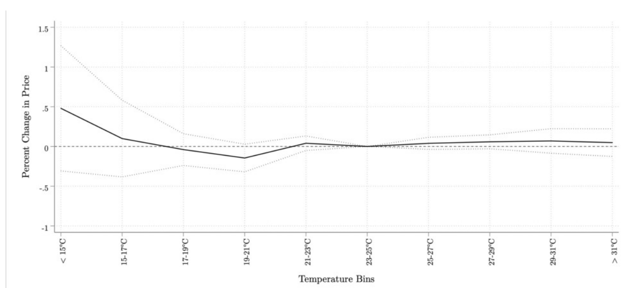
Figure A3: Temperature Bins and Agricultural Outcomes



(a) Yield



(b) Value



(c) Price

Notes: Standard errors are adjusted to account for spatial correlation (up to 1,100km), as modeled in Conley (1999) and serial correlation over time (up to a lag of 7 years), as modeled in Newey and West (1987).

A.3 Lags and Leads

Table A3: Controlling for Lags and Leads

	log Agricultural Outcomes		
	Yield (All Crops)	Value (All Crops)	Price (All Crops)
Daily Average Temperature (°C)	-0.122***	-0.123***	-0.00158
	(0.0296)	(0.0270)	(0.00949)
1-Year Lag	No	No	No
1-Year Lead	No	No	No
Daily Average Temperature (°C)	-0.104***	-0.113***	-0.00831
	(0.0238)	(0.0231)	(0.0101)
1-Year Lag	Yes	Yes	Yes
1-Year Lead	Yes	Yes	Yes
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	10,275	10,275	10,275

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation 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.

A.4 Examining the Relative Importance of Temperature for Agricultural Production in India

In the main analysis I argue that temperature is an important driver of agricultural production in India and that its omission from empirical analysis has economically meaningful consequences. This section provides supporting evidence in support of this conjecture.

In Table A4 I explore the potential for omitted variable bias induced by not controlling for temperature, or rainfall when estimating the effects of weather on agricultural productivity in India. Column (1), replicated from Table 1 in the main text presents the estimated effects of rainfall and temperature on agricultural yields. A one standard deviation increase in temperature (0.343°C) is associated with a 4.15% reduction in yields. A one standard deviation reduction in rainfall (184 mm) is associated with a 2.07% reduction in yields. In column (2) I explore the effects of temperature on yields, omitting rainfall. The estimated effect for temperature increases from -12.2%/1°C ($p<0.01$) to -13.9%/1°C ($p<0.01$) a 14% increase in magnitude. In column (3) I estimate the effects of rainfall on yields, omitting temperature. The estimated effect increases from 1.13%/100mm ($p < 0.01$) to 1.86%/100mm ($p < 0.01$) a 65% increase in the magnitude of the coefficient. The exclusion of temperature from the regression has a meaningful effect on the estimate effect of rainfall. This insight is robust to using the University of Delaware Rainfall and Temperature dataset, commonly used in the existing literature (Table A5 and A6), and to using the rainfall shock measure, introduced by Jayachandran (2006), also commonly used in the existing literature (Table A7 and A8). I also show that the relative importance of temperature holds, when accounting for the interaction between rainfall and temperature (Table A9) and when we restrict our attention to the main crop produced within each district (Table A10).

One explanation for the discrepancy with prior work is that the relationship between weather and agricultural productivity has evolved over time. Much of the existing work has focused on earlier time periods (Townsend, 1994; Kochar 1999; Jayachadran, 2006; Adhvaryu et al. (2013); Kaur, 2019). If rainfall mattered more during this period that would explain the discrepancy between the findings here and the existing literature. However, in Figures A4 and A5 we see that the omitted variable bias induced by not accounting for temperature holds in earlier periods as well. Splitting the data in 1991 the point at which India went through substantial trade liberalization reforms we observe that the effect of temperature on yields and prices are very similar over time, and whether we control for rainfall or not. The effect of rainfall on yields and prices are substantially smaller both prior to and after the 1991 reforms, when we control for temperature. Indeed the estimated effects of rainfall prior to 1991 do not appear to have a statistically significant effect prior to 1991, suggesting that rainfall was *less* important during this period. This insight holds when I do not control for temperature. The estimated effects of rainfall on yields almost double but the estimated effect in the earlier period is not larger than the estimated effect in the post-liberalization period.

Another explanation for the relative importance of temperature might be that higher temperatures are more difficult to manage than low rainfall realizations. Rainfall is storable and can be substituted with surface or ground water resources (manually, or through the use of irrigation systems). By contrast, the effects of temperature are more difficult to address, requiring heat-resistant crop varieties. Evidence to date suggests that farmers have struggled to adapt to short-run and long-run changes in temperature, even in developed countries like the United States (Burke and Emerick, 2016, Taraz, 2017, 2018).

In Table A11 I estimate that greater access to irrigation is associated with significantly lower rainfall effects. Evaluated at the mean (49%) the effects of rainfall are mitigated by almost 50%. In areas with 100% irrigation coverage, rainfall does not appear to have any effect on yields. By contrast, greater access to irrigation does not appear to be associated with meaningful reductions in the effects of temperature. Consistent with the premise that market are well integrated during the study period, I do not observe any moderating effects of irrigation on the rainfall-price or temperature-price relationship.

In Table A12 we explore the robustness of these findings to omitting rainfall or temperature from the regression. As in the main analysis we observe that the exclusion of rainfall from the estimation does not have a meaningful effect on the estimated effects of temperature. As before, the exclusion of temperature increases the magnitude of the rainfall effect. This also has meaningful implications for the interpretation of the irrigation results. When temperature is included rainfall has no effect on yields in locations with 100% irrigation coverage. When temperature is omitted, the complete irrigation is only able to mitigate 60% of the effect that rainfall has on yields. The exclusion of temperature not only overstates the importance of rainfall but undermines the estimated efficacy of irrigation. Taken at face value, this could induce over-utilization of irrigation.

I also present evidence to suggest that irrigation could help to explain the increasing importance of rainfall over time. The share of area irrigated has increased over time from 31% in 1980 to 47% in 2009, an increase of 0.64%/year (Figure A6). The effectiveness of irrigation over time is believed to have decreased due to increasing water scarcity Sekhri, 2011; 2014; Blakeslee et al. 2019. In Table A13 we see that in the pre-liberalization period greater access to irrigation was significantly more effective in mitigating the effects of rainfall on crop yields. Evaluated at the mean in the pre-liberalization period (34%) the effects of rainfall are mitigated by almost 90%. By contrast, in the post-liberalization period, during which ground water extraction and irrigation use expanded substantially, the effects of rainfall are mitigated by 60%, when evaluated at the mean (46%). It is important to caveat that all of the results, exploring the potential of irrigation in this context should be interpreted cautiously as effect moderators, rather than causal moderators. We cannot rule out that there could be other time-varying confounders that could bias the estimated effects.

Table A4: The Effect of Temperature and Rainfall on Agricultural Yields With and Without Controls

	(1) log Yield (All Crops)	(2) log Yield (All Crops)	(3) log Yield (All Crops)
Daily Average Temperature (°C)	-0.122*** (0.0296)	-0.139*** (0.0291)	
Monsoon Rainfall (100mm)	0.0113*** (0.00351)		0.0186*** (0.00369)
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	10,275	10,275	10,275

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987) (up to 7 years). District distances are computed from district centroids.

Table A5: The Effect of Temperature and Rainfall on Agricultural Yields, Value, and Prices (UDEL Data)

	(1) Yield (All Crops)	(2) Value (All Crops)	(3) Price (All Crops)
Daily Average Temperature (°C)	-0.127***	-0.120***	0.00683
	(0.0333)	(0.0318)	(0.00955)
Monsoon Rainfall (100mm)	0.0212***	0.0168***	-0.00442**
	(0.00347)	(0.00366)	(0.00203)
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	10,275	10,275	10,275

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987) (up to 7 years). District distances are computed from district centroids.

Table A6: The Effect of Temperature and Rainfall on Agricultural Yields With and Without Controls (UDEL Data)

	(1) Yield (All Crops)	(2) Yield (All Crops)	(3) Yield (All Crops)
Daily Average Temperature (°C)	-0.127***	-0.158***	
	(0.0333)	(0.0337)	
Monsoon Rainfall (100mm)	0.0212***		0.0274***
	(0.00347)		(0.00389)
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	9,981	9,981	9,981

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987) (up to 7 years). District distances are computed from district centroids.

Table A7: The Effect of Temperature and Rainfall Shocks on Agricultural Yields, Value, and Prices

	(1) Yield (All Crops)	(2) Value (All Crops)	(3) Price (All Crops)
Daily Average Temperature (°C)	-0.116***	-0.116***	-0.000529
	(0.0263)	(0.0245)	(0.00913)
Monsoon Rainfall (Shock)	0.0514***	0.0487***	-0.00279
	(0.0104)	(0.0105)	(0.00532)
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	10,275	10,275	10,275

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987) (up to 7 years). District distances are computed from district centroids.

Table A8: The Effect of Temperature and Rainfall Shocks on Agricultural Yields With and Without Controls

	(1) Yield (All Crops)	(2) Yield (All Crops)	(3) Yield (All Crops)
Daily Average Temperature (°C)	-0.116***	-0.139***	
	(0.0263)	(0.0291)	
Monsoon Rainfall (Shock)	0.0514***		0.0719***
	(0.0104)		(0.0136)
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	10,275	10,275	10,275

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987) (up to 7 years). District distances are computed from district centroids.

Table A9: The Effect of Temperature, Rainfall, and the Interaction Between Temperature and Rainfall on Agricultural Yields, Value, and Prices

	(1) Yield (All Crops)	(2) Value (All Crops)	(3) Price (All Crops)
Daily Average Temperature (°C)	-0.119***	-0.119***	-0.000886
	(0.0285)	(0.0261)	(0.00952)
Monsoon Rainfall (100mm)	0.0112***	0.00963***	-0.00152
	(0.00356)	(0.00342)	(0.00169)
Temperature × Rainfall	0.00152	0.00188**	0.000362
	(0.000982)	(0.000945)	(0.000408)
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	10,275	10,275	10,275

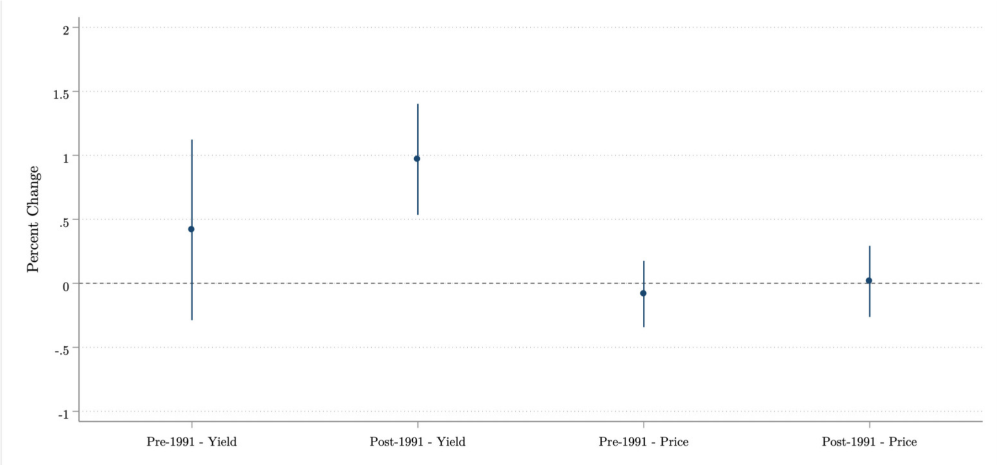
Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Temperature and rainfall are demeaned so that the interaction term captures the interaction of deviations from average temperature and average rainfall. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987) (up to 7 years). District distances are computed from district centroids.

Table A10: The Effect of Temperature and Rainfall on Agricultural Yields, Value, and Prices (Main Crop)

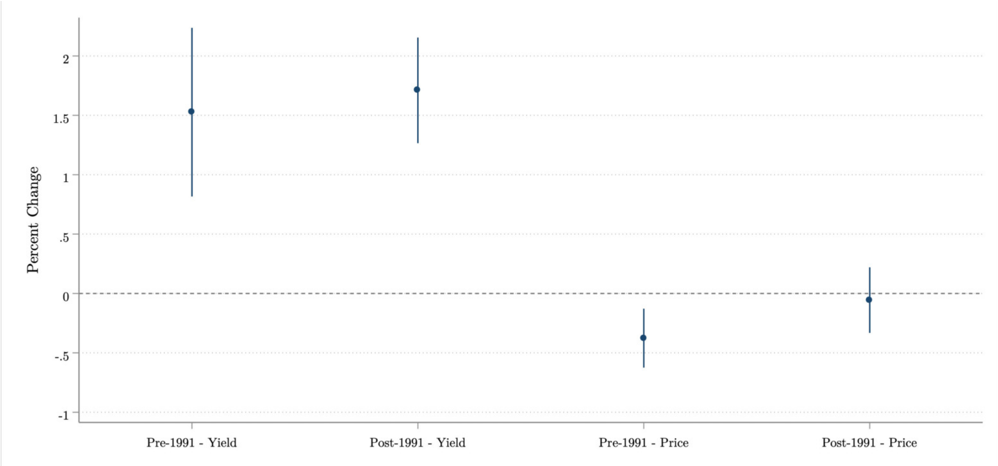
	(1) Yield (Main Crop)	(2) Value (Main Crop)	(3) Price (Main Crop)
Daily Average Temperature (°C)	-0.165*	-0.162**	0.00259
	(0.0974)	(0.0764)	(0.0348)
Monsoon Rainfall (100mm)	0.0155*	0.00957	-0.00597
	(0.00925)	(0.00845)	(0.00456)
Fixed Effects	District, Year and State-Year Time Trends		
Observations	1,551	1,551	1,551

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987) (up to 7 years). District distances are computed from district centroids.

Figure A4: The Effects of a 100mm Increase in Monsoon Rainfall on Crop Yields and Prices, Before and After Trade Liberalization



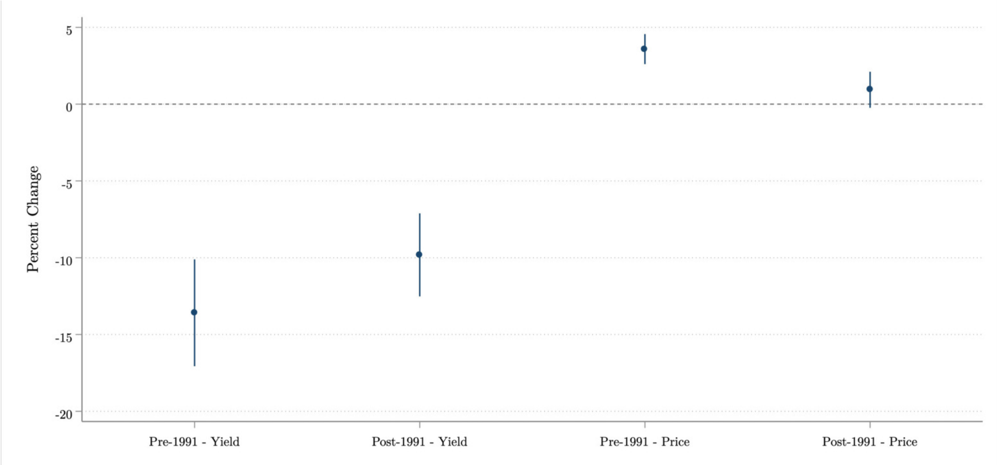
(a) Temperature Controls



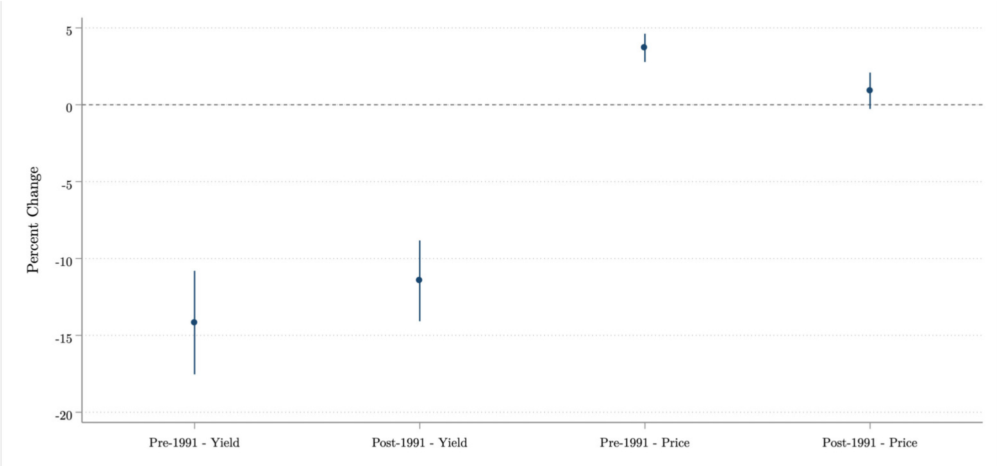
(b) No Temperature Controls

Notes: Standard errors are adjusted to account for spatial correlation (up to 1,100km), as modeled in Conley (1999) and serial correlation over time (up to a lag of 7 years), as modeled in Newey and West (1987).

Figure A5: The Effects of a 1°C Increase in Temperature on Crop Yields and Prices, Before and After Trade Liberalization



(a) Rainfall Controls



(b) No Rainfall Controls

Notes: Standard errors are adjusted to account for spatial correlation (up to 1,100km), as modeled in Conley (1999) and serial correlation over time (up to a lag of 7 years), as modeled in Newey and West (1987).

Table A11: Irrigation and the Effect of Temperature and Rainfall on Agricultural Yields, Value, and Prices

	(1) Yield (All Crops)	(2) Value (All Crops)	(3) Price (All Crops)
Daily Average Temperature (°C)	-0.136***	-0.140***	-0.00379
	(0.0342)	(0.0315)	(0.0102)
DAT × Irrigation Share	0.0212	0.0262*	0.00496
	(0.0152)	(0.0152)	(0.00627)
Monsoon Rainfall (100mm)	0.0179***	0.0153***	-0.00258
	(0.00422)	(0.00437)	(0.00210)
Rain × Irrigation Share	-0.0168**	-0.0138*	0.00304
	(0.00764)	(0.00729)	(0.00325)
Irrigation Share	-0.112	-0.342	-0.230
	(0.372)	(0.379)	(0.174)
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	10,275	10,275	10,275

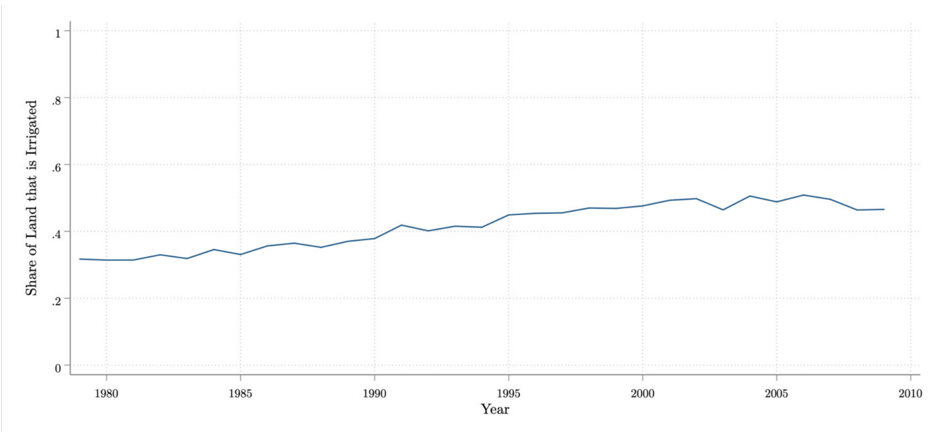
Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987) (up to 7 years). District distances are computed from district centroids.

Table A12: Irrigation and the Effect of Temperature and Rainfall on Agricultural Yields With and Without Controls

	(1) Yield (All Crops)	(2) Yield (All Crops)	(3) Yield (All Crops)
Daily Average Temperature (°C)	-0.136***	-0.151***	
	(0.0342)	(0.0339)	
DAT × Irrigation Share	0.0212	0.0258	
	(0.0152)	(0.0159)	
Monsoon Rainfall (100mm)	0.0179***		0.0242***
	(0.00422)		(0.00506)
Rain × Irrigation Share	-0.0168**		-0.0146*
	(0.00764)		(0.00762)
Irrigation Share	-0.112	-0.319	0.431***
	(0.372)	(0.393)	(0.0873)
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	10,275	10,275	10,275

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987) (up to 7 years). District distances are computed from district centroids.

Figure A6: The Share of Land that is Irrigated Over Time (1979-2009).



Notes: The share of irrigated land is defined as the total area in ’000 hectares that is irrigated by canals, tanks, tubewells, other wells, or other sources, divided by the total area planted in ’000 hectares.

Table A13: Irrigation and the Effect of Temperature and Rainfall on Agricultural Yields Over Time

	(1) Yield (All Crops)	(2) Yield (All Crops)	(3) Yield (All Crops)
Daily Average Temperature (°C)	-0.101***	-0.158***	-0.100***
	(0.0111)	(0.0207)	(0.0144)
DAT × Irrigation Share	-0.000934	0.0317*	-0.000183
	(0.00456)	(0.0181)	(0.00449)
Monsoon Rainfall (100mm)	0.0185***	0.0171***	0.0201***
	(0.00250)	(0.00404)	(0.00292)
Rain × Irrigation Share	-0.0265***	-0.0448***	-0.0248***
	(0.00429)	(0.00812)	(0.00494)
Irrigation Share	0.323***	-0.369	0.369***
	(0.118)	(0.433)	(0.118)
Years	All	Pre-1991	Post-1991
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	49,925	20.606	29,319

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,100km) as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987) (up to 7 years). District distances are computed from district centroids.

B Theory Appendix – Labor Reallocation and Market Integration

This appendix presents a simple specific factors model based on Matsuyama (1992), demonstrating how the direction of labor reallocation in response to a sector-specific productivity shock depends on market integration. Any analysis of labor reallocation across sectors within an economy necessitates a diversified economy and so for simplicity I consider two sectors: agriculture (a) and manufacturing (m).

Preferences

Consider a country composed of a large number of regions i. Each location i is populated by a continuum of workers L_i, which are assumed to be mobile between sectors, immobile between regions, supplied inelastically, and fully employed. Workers earn income $w_{ij}L_{ij}$ and preferences are defined over two types of goods agriculture and manufactured goods. Agricultural consumption is subject to subsistence constraints with a Stone-Geary utility function (Matsuyama, 1992; Caselli and Coleman, 2001; Jayachandran, 2006; Desmet and Parente, 2012).[21] Given prices in sector j, p_{ij}, and total income, w_iL_i, each worker maximizes

$$U_i = (C_{ia} - \bar{a})^{\alpha} {C_{im}}^{1-\alpha} \tag{5}$$

which they maximize subject to their budget constraint,

$$p_{ia}C_{ia} + p_{im}C_{im} \leq L_i w_i \tag{6}$$

Worker demand for goods in agriculture, $D_{ia} = p_{ia}\bar{a} + \alpha(L_i w_i - p_{ia}\bar{a})$. For manufactured goods $D_{im} = (1-\alpha)(L_i w_i - p_{ia}\bar{a})$. As such, preferences are non-homothetic. Higher food subsistence requirements, higher prices, and lower incomes are associated with an increase in the demand for agricultural goods ($D_{ia}/L_i w_i$).

Production

There are 2 goods that can be produced in each location i: agricultural good a and manufactured goods m.[22] I assume that all regions have access to the same technology and so

[21] Non-homothetic preferences can also be incorporated through a CES utility function where the elasticity of substitution between agricultural goods and other goods is less than one (Ngai and Pissarides, 2007; Desmet and Rossi-Hansberg, 2014).

[22] I will refer to goods and sectors interchangeably.

production functions do not differ across regions within each industry. Different industries may have different production functions. I drop the locational subscript unless necessary.

Output of each good j is produced according to the following production function,

$$Y_j = A_j F_j(L_j) \tag{7}$$

where A_j is sector-specific productivity and L_j is the set of workers in sector j. I assume that $F_j(0) = 0$, $F_j{}' > 0$ and $F_j{}'' < 0$. In addition, I assume that $A_a F^1(1) > \bar{a}L > 0$. This inequality states that agriculture is productive enough to provide the subsistence level of food to all workers. If this condition is violated then workers receive negative infinite utility.

Each firm equates its demand for labor to the value of the marginal product of labor. As market clearing requires that $L_a + L_m = L$, the marginal productivity of labor will be equalized across sectors,

$$p_a A_a F_a{}'(L_a) = w = p_m A_m F_m{}'(L_m) \tag{8}$$

Equilibrium

Autarky and Equilibrium Prices

Equilibrium is defined as a set of prices, wages, and an allocation of workers across sectors such that goods and labor markets clear. In a state of autarky, the price ensures that the total amount produced is equal to total consumption in each location, so that,

$$\begin{aligned} C_a &= A_a F_a(L_a) \qquad (9) \\ C_m &= A_m F_m(L_m) \end{aligned}$$

Maximization of equation 5 implies that each worker consumes agricultural goods such that,

$$p_a C_a = \bar{a} + \frac{\alpha p_m C_m}{1-\alpha} \tag{10}$$

Combining this result with the profit maximization condition (equation 8), the labor market clearing condition ($L_m = 1 - L_a$), and the fact that total production must equal total consumption yields,

$$\Omega(L_m) = \frac{\bar{a}}{A_a} \tag{11}$$

where,

$$\Omega(L_m) \equiv F_m(L_m) - \frac{{F_m}'(L_m)F_a(1-L_a)}{{F_a}'(1-L_a)} \tag{12}$$

In addition, it is the case that $\Omega(0) = F_m(1)$, $\Omega(1) < 0$ and $\Omega'(\cdot) < 0$.

In equilibrium a unique interior solution will arise for the employment share in manufacturing L_m,

$$L_m = \Omega^{-1}\left(\frac{\bar{a}}{A_a}\right) \tag{13}$$

As preferences are non-homothetic, the demand for agricultural goods (food) decreases as income increases (Engel's law). An increase (decrease) in agricultural productivity will push (pull) workers into the manufacturing (agricultural) sector. Similarly, a decrease (increase) in the subsistence constraint $\bar{a}$ will push (pull) workers into the manufacturing (agricultural) sector.

Trade and Equilibrium Prices

Without opportunities to trade, consumers must consume even their worst productivity draws. The ability to trade breaks the production-consumption link. In the case of free trade, prices, set globally, are taken as given. If the world price for a good j, $\bar{p}_j$, exceeds the autarkic local price p_{ij}, firms and farms will engage in arbitrage and sell to the global market. By contrast, if the world price for a good j is less than the autarkic local price, consumers will import the product from outside of the local market. Local demand does not affect the allocation of labor across sectors, i.e., changes in A_{ij} do not affect prices.

As discussed above, the rest of the world differs only in terms of agricultural and manufacturing productivity, $A_{i'a}$ and $A_{i'm}$. Profit maximisation in the rest of the world implies that,

$$p_a A_{i'a} {F_{i'a}}'(L_{i'a}) = p_m A_{i'm} {F_{i'm}}'(L_{i'm}) \tag{14}$$

Within industry, production functions are assumed to be constant across regions. Under the assumption of free trade and incomplete specialisation, manufacturing employment in region i, L_{im}, is now determined jointly by equations 8 and 14. Taking the ratio of these equations provides the following equality,

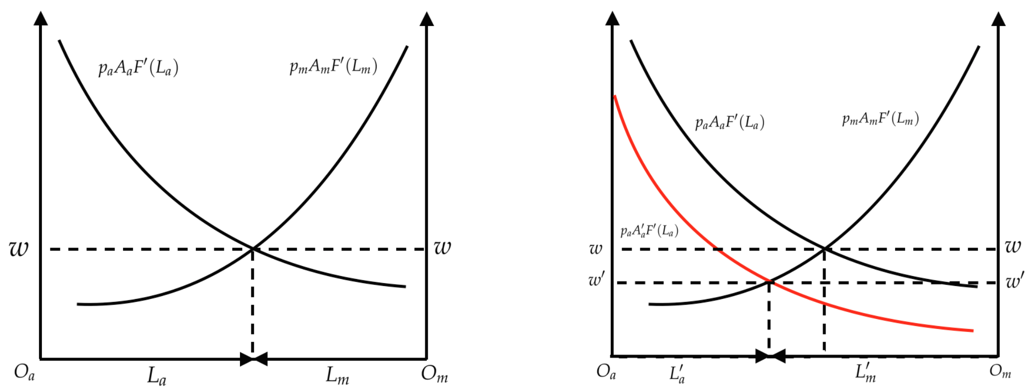
$$\frac{{F_{im}}'(L_{im}}{{F_{ia}}'(L_{ia})} = \frac{A_{ia}A_{i'm}}{A_{i'a}A_{im}} \frac{{F_{i'm}}'(L_{i'm})}{{F_{i'a}}'(L_{i'a})} \tag{15}$$

As $\frac{{F_{im}}'(L_{im})}{{F_{ia}}'(L_{ia})}$ is decreasing in L_{im} it follows that,

$$L_{im} \gtreqless L_{ia} \quad iff \quad \frac{A_{i'a}}{A_{i'm}} \gtreqless \frac{A_{ia}}{A_{im}} \tag{16}$$

In this case an increase (decrease) in agricultural productivity will pull (push) workers into the agricultural (manufacturing) sector, due to a change in local comparative advantage. This is demonstrated in FigureB1

Figure B1: The Effect of a Reduction in Agricultural Productivity on Equilibrium Employment Shares (Free Trade)



In the case of costly trade, firms (farms) will engage in arbitrage opportunities as before; however, the local price is bounded by a trade cost δ. A trader will engage in arbitrage, selling on the global market, as long as the global price is greater than the local price net of trade costs, i.e., $\bar{p}_j/\delta > p_j^A$. Conversely, consumers will import from the global market if the local price is greater than the global price net of trade costs, i.e., $\bar{p}_j < p_j^A/\delta$. In the case of homogenous traders where all agents face a constant iceberg trade cost, the local price is bounded by the global price, i.e., $\frac{\bar{p}_j}{\delta} \leq p_j^A \leq \bar{p}_j\delta$.

C The Effects of Weather on Local Labor Markets: Supporting Evidence

C.1 NSS Data Appendix

This section provides additional details on the NSS Employment and Unemployment surveys used in section III. The National Sample Survey Organization (NSSO) carries out all-India, large-sample household surveys on employment and unemployment every few years. This paper takes advantage of the 60th round (January 2004 – June 2004), the 61st round (July 2004 – June 2005), the 62nd round (July 2005 – June 2006), and the 64th round (July 2007 – June 2008).

Using this data I construct the average day wage and district employment shares for agricultural workers, manufacturing workers, services workers and construction workers. Looking at the breakdown of employment between rural and urban areas, it is clear that non-agricultural activities are not restricted to urban areas.

Table C1: Labor Force Shares in India

	Rural	Urban	Combined
Agriculture	67.2%	13%	58.4%
Manufacturing	9.1%	20.2%	10.8%
Services	13.5%	49.1%	20%
Construction	8%	13.2%	8.3%
Unemployment	2.2%	4.5%	2.5%

Agricultural employment the most important sector in rural areas, accounting for 67% of rural employment, on average. Manufacturing and services employment are the most important sectors in urban areas accounting for 70% of urban employment, on average. A non-trivial share of employment in rural areas is non-agricultural. This is consistent with one of the most striking features of India's recent spatial development, namely the expansion of India's metropolitan areas into rural areas, referred to as peri-urbanization.[23] In the last decade there has been an official increase in urban agglomerations by 25%, with populations shifting outwards. Henderson (2010) presents evidence in support of this industrial decentralization for the Republic of Korea and Japan. Desmet et al. (2015) and Ghani et al. (2014) also provide supporting evidence for this process in India. Desmet et al. (2015) show that the services sector has become increasingly concentrated over time, while manufacturing has become less concentrated in districts that were already concentrated, and has

[23] See Colmer (2015) for a more detailed discussion and review of this literature

increased in districts which originally were less concentrated. Ghani et al. (2014) look more specifically at the manufacturing sector and document its movement away from urban to rural areas, comparing the formal and informal sectors. The authors argue that the formal sector is becoming more rural; however, in practice, a lot of this movement is likely sub-urbanization, rather than ruralization, in which firms move to the outskirts of urban areas where they can exploit vastly cheaper land and somewhat cheaper labor. Colmer (2015) finds evidence consistent with these papers, finding that manufacturing employment growth has become more concentrated in districts which were initially less concentrated, and that this employment growth is significantly higher in less concentrated rural areas compared to less concentrated urban areas.

This process of peri-urbanization also benefits workers, reducing the cost of sectoral adjustment and migration. Indeed, in many instances, it may reduce the need to migrate altogether, with workers choosing to commute from home rather than migrate to urban areas. This is consistent with the non-trivial shares of manufacturing employment and agricultural employment present in both rural and urban areas. Interestingly, we observe that the unemployment share in urban areas is almost twice the size of those in rural areas, suggesting that there is more absorptive capacity in rural areas.

Table C2: Descriptive Statistics - Local Labor Markets in India (2004–2007)

	Mean	Std. Dev. (within)	Std. Dev. (between)
Panel A: Wage Data			
Average Day Wage: Agriculture	52.712	17.425	19.963
Average Day Wage: Manufacturing	98.399	47.087	49.196
Average Day Wage: Services	159.012	45.538	40.159
Average Day Wage: Construction	79.239	35.566	30.400
Panel B: Employment Data			
District Employment Share: Agriculture	0.550	0.081	0.169
District Employment Share: Manufacturing	0.113	0.041	0.075
District Employment Share: Services	0.220	0.050	0.089
District Employment Share: Construction	0.083	0.041	0.048
Unemployment Share of Labor Force	0.032	0.019	0.025
Panel C: Meteorological Data			
Daily Average Temperature (°C)	25.280	0.236	3.491
Monsoon Rainfall (mm)	978.71	189.59	485.18

C.2 Additional Results and Robustness Tests

C.2.1 The Relative Importance of Temperature vs. Rainfall for Wages and Employment in India

Table C3: The Effect of Temperature on Wages Without Rainfall Controls

	log Average Day Wages			
	Agriculture	Manufacturing	Services	Construction
Daily Average Temperature (°C)	-0.0989** (0.0467)	-0.0476 (0.0578)	-0.0491 (0.0427)	-0.00283 (0.0402)
Fixed Effects	District, Year, State-Year Time Trends			
Observations	1,062	1,062	1,062	1,062

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids. Differences in observations across sectors arise due to missing wage data.

Table C4: The Effect of Rainfall on Wages Without Temperature Controls

	log Average Day Wages			
	Agriculture	Manufacturing	Services	Construction
Monsoon Rainfall (100mm)	0.00106	-0.0107	0.00685	0.00556
	(0.00445)	(0.00927)	(0.00791)	(0.00659)
Fixed Effects	District, Year, State-Year Time Trends			
Observations	1,062	1,062	1,062	1,062

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids. Differences in observations across sectors arise due to missing wage data.

Table C5: The Effect of Weather on Wages (UDEL Data)

	log Average Day Wages			
	Agriculture	Manufacturing	Services	Construction
Daily Average Temperature (°C)	-0.0694 (0.0454)	-0.0382 (0.0573)	-0.0244 (0.0591)	0.0384 (0.0452)
Monsoon Rainfall (100mm)	0.00654 (0.00676)	0.0157* (0.00919)	-0.000192 (0.00740)	0.00411 (0.00592)
Fixed Effects	District, Year, State-Year Time Trends			
Observations	1,062	1,062	1,062	1,062

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids. Differences in observations across sectors arise due to missing wage data.

Table C6: The Effect of Temperature on Wages Without Rainfall Controls (UDEL)

	log Average Day Wages			
	Agriculture	Manufacturing	Services	Construction
Daily Average Temperature (°C)	-0.0891** (0.0416)	-0.0852 (0.0527)	-0.0239 (0.0551)	0.0261 (0.0390)
Fixed Effects	District, Year, State-Year Time Trends			
Observations	1,062	1,062	1,062	1,062

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids. Differences in observations across sectors arise due to missing wage data.

Table C7: The Effect of Rainfall on Wages Without Temperature Controls (UDEL)

	log Average Day Wages			
	Agriculture	Manufacturing	Services	Construction
Monsoon Rainfall (100mm)	0.0109*	0.0181**	0.00135	0.00168
	(0.00645)	(0.00839)	(0.00696)	(0.00517)
Fixed Effects	District, Year, State-Year Time Trends			
Observations	1,062	1,062	1,062	1,062

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids. Differences in observations across sectors arise due to missing wage data.

Table C8: The Effects of Temperature on the District Labor Force Share of Employment - By Sector (No Rainfall Controls)

	District Labor Force Shares				
	Agriculture	Manufacturing	Services	Construction	Unemployment
Daily Average Temperature (°C)	-0.0583*** (0.0133)	0.0155** (0.00666)	0.0302*** (0.00742)	0.00906* (0.00535)	0.00356 (0.00277)
Fixed Effects	District, Year, 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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids.

Table C9: The Effects of Rainfall on the District Labor Force Share of Employment - By Sector (No Temperature Controls)

	District Labor Force Shares				
	Agriculture	Manufacturing	Services	Construction	Unemployment
Monsoon Rainfall (100mm)	0.00211 (0.00205)	-0.000287 (0.000874)	-0.00178 (0.00139)	-0.000441 (0.00103)	0.000399 (0.000390)
Fixed Effects	District, Year, 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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids.

Table C10: The Effects of Weather on the District Labor Force Share of Employment - By Sector (UDEL)

	District Labor Force Shares				
	Agriculture	Manufacturing	Services	Construction	Unemployment
Daily Average Temperature (°C)	-0.0621***	0.00727	0.0317***	0.0191**	0.00406
	(0.0157)	(0.00607)	(0.00998)	(0.00782)	(0.00296)
Monsoon Rainfall (100mm)	-0.00116	-0.000141	-0.000329	0.00183	-0.000203
	(0.00249)	(0.00129)	(0.00173)	(0.00128)	(0.000588)
Fixed Effects	District, Year, 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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids.

Table C11: The Effects of Temperature on the District Labor Force Share of Employment - By Sector (UDEL)

	District Labor Force Shares				
	Agriculture	Manufacturing	Services	Construction	Unemployment
Daily Average Temperature (°C)	-0.0586*** (0.0135)	0.00769 (0.00506)	0.0327*** (0.00892)	0.0135** (0.00678)	0.00467* (0.00265)
Fixed Effects	District, Year, 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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids.

Table C12: The Effects of Rainfall on the District Labor Force Share of Employment - By Sector (UDEL)

	District Labor Force Shares				
	Agriculture	Manufacturing	Services	Construction	Unemployment
Monsoon Rainfall (100mm)	0.00276 (0.00227)	-0.000600 (0.00111)	-0.00233 (0.00163)	0.000631 (0.00114)	-0.000459 (0.000533)
Fixed Effects	District, Year, 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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids.

C.2.2 Alternative Measures of Employment

Table C13: The Effects of Weather on the District Labor Force Share of Employment - By Sector (Principal Sector of Employment)

	District Labor Force Shares				
	Agriculture	Manufacturing	Services	Construction	Unemployment
Daily Average Temperature (°C)	-0.0416** (0.0168)	0.0107 (0.00837)	0.0215** (0.0100)	0.0121* (0.00644)	-0.00259 (0.00297)
Monsoon Rainfall (100mm)	-0.000230 (0.00188)	-0.000193 (0.000989)	0.000292 (0.00165)	0.0000725 (0.00103)	0.0000579 (0.000396)
Fixed Effects	District, Year, 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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids.

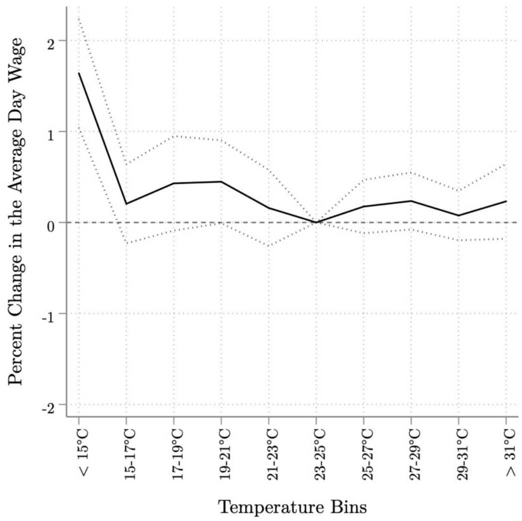
C.2.3 Non-Linearities in the Temperature Schedule

Table C14: The Effects of Daily Temperature on Wages

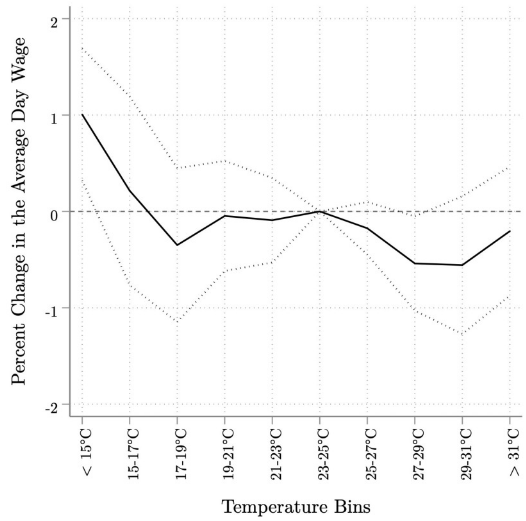
	(1) Agriculture	(2) Manufacturing	(3) Services	(4) Construction
Degree Days (10 days)	0.00178	-0.000908	-0.0000676	0.00144
$t_L = 23, t_H = \infty$	(0.00182)	(0.00247)	(0.00173)	(0.00152)
Degree Days (10 days)	-0.0117***	-0.00665**	-0.00215	-0.000371
$t_L = 0, t_H = 23$	(0.00364)	(0.00281)	(0.00218)	(0.00162)
Rainfall Controls	Yes	Yes	Yes	Yes
Fixed Effects	District, Year and State-Year Time Trends			
Observations	1,062	1,062	1,062	1,062

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987). District distances are computed from district centroids.

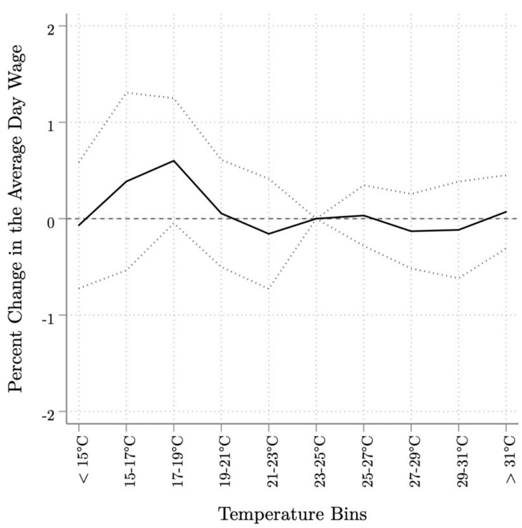
Figure C1: Temperature Bins and Wages



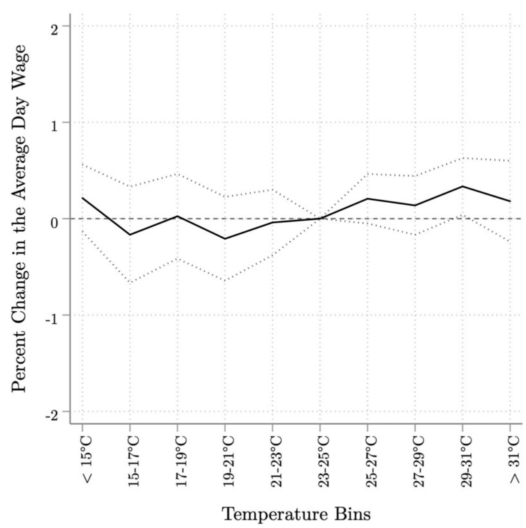
(a) Agriculture



(b) Manufacturing



(c) Services



(d) Construction

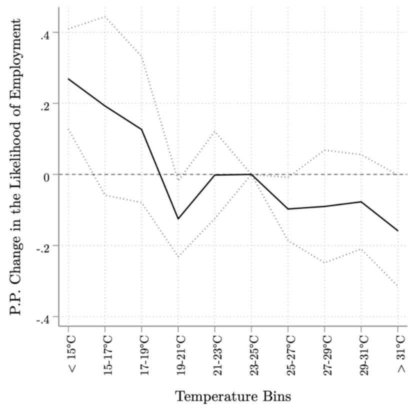
Notes: Standard errors are adjusted to account for spatial correlation (up to 1,100km), as modeled in Conley (1999) and serial correlation over time (up to a lag of 7 years), as modeled in Newey and West (1987).

Table C15: The Effects of Daily Temperature on Employment

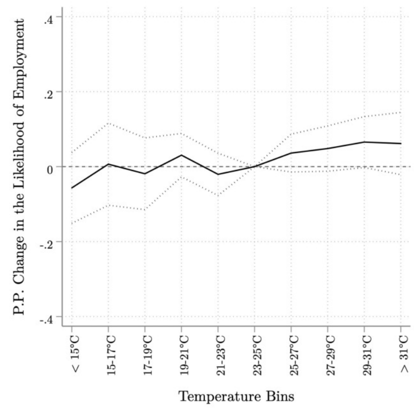
	(1) Agriculture	(2) Manufacturing	(3) Services	(4) Construction	(5) Unemployed
Degree Days (10 days)	-0.00154**	0.000697**	0.000346	0.0000367	-0.0000134
$t_L = 23, t_H = \infty$	(0.000632)	(0.000325)	(0.000335)	(0.000235)	(0.00000978)
Degree Days (10 days)	-0.00266***	0.000321	0.00181***	0.000231	0.0000413
$t_L = 0, t_H = 23$	(0.000641)	(0.000305)	(0.000373)	(0.000321)	(0.0000145)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	District, Year, and State-Year Time Trends				
Observations	1,062	1,062	1,062	1,062	1,062

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,000km) as modeled in Conley (1999) and serial correlation (1-year) as modeled in Newey and West (1987). District distances are computed from district centroids. Kernels are selected to provide the most conservative standard errors, looped over all distances between 10 and 2,000km and 1–7 years. Results are also robust to using cluster robust standard errors at the state level.

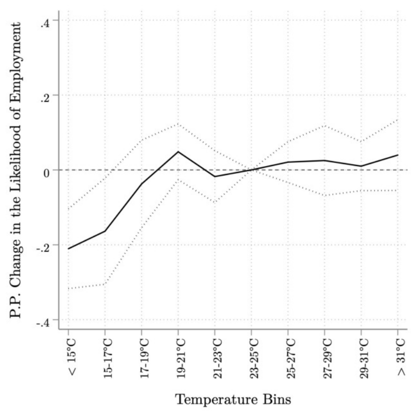
Figure C2: Temperature Bins and Employment



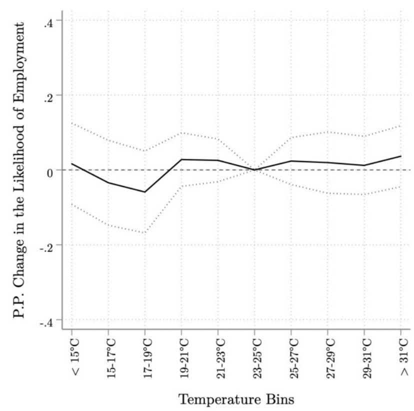
(a) Agriculture



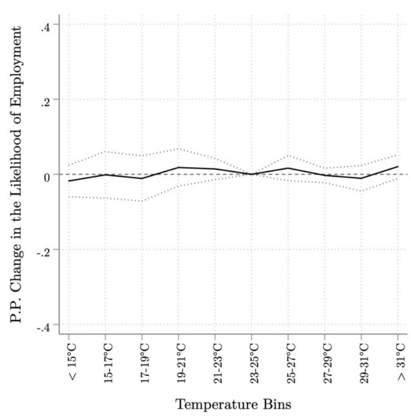
(b) Manufacturing



(c) Services



(d) Construction



(e) Unemployment

Notes: Standard errors are adjusted to account for spatial correlation (up to 1,100km), as modeled in Conley (1999) and serial correlation over time (up to a lag of 7 years), as modeled in Newey and West (1987).

C.2.4 Lags and Leads

Table C16: The Effects of Weather on Average Wages

	log Average Day Wages			
	Agriculture	Manufacturing	Services	Construction
Daily Average Temperature (°C)	-0.134** (0.0538)	-0.120* (0.0676)	-0.0348 (0.0532)	0.0238 (0.0431)
1-Year Lag	No	No	No	No
1-Year Lead	No	No	No	No
Daily Average Temperature (°C)	-0.107** (0.0435)	-0.0850 (0.0809)	-0.0274 (0.0413)	0.0183 (0.0414)
1-Year Lag	Yes	Yes	Yes	Yes
1-Year Lead	Yes	Yes	Yes	Yes
Fixed Effects	District, Year, State-Year Time Trends			
Observations	1,062	1,062	1,062	1,062

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation 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. Differences in observations across sectors arise due to missing wage data.

Table C17: The Effects of Weather on the District Labor Force Share of Employment - By Sector

	District Labor Force Shares				
	Agriculture	Manufacturing	Services	Construction	Unemployment
Daily Average Temperature (°C)	-0.0714*** (0.0165)	0.0204** (0.00867)	0.0335*** (0.00953)	0.0105 (0.00673)	0.00700* (0.00370)
1-Year Lag	No	No	No	No	No
1-Year Lead	No	No	No	No	No
Daily Average Temperature (°C)	-0.0664*** (0.0169)	0.0198*** (0.00744)	0.0291*** (0.00865)	0.0114** (0.00540)	-0.00417* (0.00249)
1-Year Lag	Yes	Yes	Yes	Yes	Yes
1-Year Lead	Yes	Yes	Yes	Yes	Yes
Fixed Effects	District, Year, 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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation 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.

C.2.5 The Effects of Temperature on Temporary Migration

An important consideration is the degree to which workers move across space, rather than sectors. To explore this consideration I engage in two exercises using Round 64 of the NSS Employment Survey, which contains a special schedule on seasonal migration. This provides data on the origin district of seasonal migrants; however, there is no detail on the destination of seasonal migrants. Instead, the NSS reports the destination of migrants in district ℓ_o in six relevant categories: rural or urban migration within the same district (m_{oo}); rural or urban migration between districts in the same state ($\sum_{\ell_d \neq \ell_o \in S_o} m_{od}$); rural or urban migration between states ($\sum_{S_d \neq S_o} \sum_{\ell_d \neq \ell_o \in S_d} m_{od}$). The first empirical exercise uses information on the share of workers in each district that seasonally migrate to other districts. Assuming that seasonal migration in Round 64 is representative of typical seasonal migration decisions, I interact district temperature and rainfall realizations with the share of workers in the district that migrate out of the district. If workers are wont to migrate out of district in response to weather-driven agricultural productivity shocks then we may expect that districts that experience temperature shocks should have dampened reductions in the share of workers in agriculture and exacerbated increases in the employment shares for manufacturing and services, as the population shrinks. We observe that, on average, 3.2% of rural workers migrated seasonally out of their district in the year 2007.

The second exercise combines this information with imputed information on the district of destination to examine how temperature shocks in other districts affect local labor markets through migration. Since the NSS survey does not contain information on the destination district, it is necessary to predict the district of destination for seasonal migrants who migrate to different districts. To do this, I draw inspiration from Imbert and Papp (2018) and use the 2001 Indian Population Census, extracting data on migrant workers by state of last residence. For each destination district, ℓ_d, I observe: the number of migrant workers from the same district (M_{dd}); the number of migrant workers from other districts in the same state ($\sum_{\ell_o \neq \ell_d \in S_d} M_{do}$); the number of migrant workers from districts in other states ($\sum_{S_o \neq S_d} \sum_{\ell_o \neq \ell_d \in S_o} M_{do}$). I combine these data to estimate seasonal migration flows $\hat{m}_{od}$, using the following algorithm:

$$\hat{m}_{od} = \begin{cases} m_{od} & \text{if } \ell_o = \ell_d \\ \frac{\sum_{\ell_o \neq \ell_d \in S_d} M_{do}}{\sum_{S_d} \sum_{\ell_o \neq \ell_d \in S_d} M_{do}} \sum_{\ell_d \neq \ell_o \in S_o} m_{od} & \text{if } \ell_o \neq \ell_d \text{ and } S_o = S_d \\ \frac{\sum_{S_o \neq S_d} \sum_{\ell_o \neq \ell_d \in S_o} M_{do}}{\sum_{S_d} \sum_{S_o \neq S_d} \sum_{\ell_o \neq \ell_d \in S_o} M_{do}} \sum_{S_d \neq S_o} \sum_{\ell_d \neq \ell_o \in S_d} m_{od} & \text{if } \ell_o \neq \ell_d \text{ and } S_o \neq S_d \end{cases}$$

I deviate from Imbert and Papp (2018) in two respects. First, by using migrant workers rather than the total population of permanent migrants. Second, by broadening my attention beyond urban destinations. Non-agricultural production is not restricted to urban areas, and so rural–urban migration is not the appropriate characterization of migration flows in the context of this paper. Indeed, a number of papers provide evidence to suggest that non-agricultural production in India is decentralizing, from urban to peri-urban and even rural areas, taking advantage of cheaper labor and vastly cheaper land prices (Ghani et al., 2015; Desmet et al., 2015; Colmer, 2015). These adjustments provide stronger support for the identification assumption on which this approach relies: that the proportion of NSS seasonal migrants who go from district ℓ_o to district ℓ_d, either in the same state or between states, is the same as the proportion of census migrant workers in district ℓ_d who come from another district ℓ_o, either in the same state or between states; that is, short-term and long-term migrants choose similar destinations.

Imbert and Papp (2018) provide some evidence in support of this assumption using data from the 2006 ARIS-REDS survey, which records both short and long-term migration flows for a representative sample of Indian villages. They construct bilateral migration matrices for short-term and long-term migration flows at the district-level. They estimate that, conditional on staying in the same state or going to another state, short-term and long-term migrants from the same origin choose similar destinations.

On average, rural-origin migrants comprise the bulk of migration flows, accounting for nearly 90% of all seasonal migration. 31.4% of migrants move within the same district, 33.3% of migrants move to another district within the same state (shared among an average of 28 districts per state, 1.15% per district), and 35.2% move to a different state (an average of 0.064% per district). Most strikingly, we observe that there is very little seasonal migration in absolute terms – only 4.2% of the workforce engage in seasonal migration. This is an observation that has been highlighted by a number of papers and contrasts starkly with migration patterns in other developing and developed countries (Foster and Rosenzweig, 2008; Munshi and Rosenzweig, 2016; Morten, 2019)

These insights have potential implications for the effects of localized shocks in India. First, if workers are limited in their ability to move across space, then the economic consequences of agricultural productivity shocks will be locally concentrated. Second, this implies that sectoral shocks are likely to have a bigger effect on other sectors in the local economy, as employment adjustments are less diversified across space. Finally, this implies that localized productivity shocks elsewhere are unlikely to have a large effect on economic outcomes across space; however, the validity of this argument is decreasing as the spatial correlation of localized productivity shocks increases, and as the importance of a specific location for the supply of workers increases. I test this prediction by examining the effects of localized temperature shocks in origin districts on local labor market outcomes in destination districts. This helps us to understand the degree to which transitory localized productivity shocks propagate through short-term migrants across space.

Empirical Specification – Migration

In examining the potential effects of migration across space, I present two specifications. The first exercise interacts temperature with the share of rural workers in each district that migrate out of their district for work based on data from Round 64 of the NSS employment survey,

$$Y_{dt} = f(w_{dt}) + \gamma \left[f(w_{dt}) \times \frac{m_d}{L_d} \right] + \alpha_d + \alpha_t + \phi_s t + \varepsilon_{dt}$$

This specification provides insights into the degree to which out-migration may affect local labor market outcomes in origin districts.

The second migration specification explores the degree to which weather-driven changes in agricultural productivity in origin districts affect local labor market outcomes in destination districts through migration. Using the bilateral migration flows described above, I construct a spatial weights matrix summarizing the migratory relationship between each district. As mentioned, migration flows between ℓ_o and ℓ_d produce an $o \times d$ matrix $\mathbf{M}_{o\times d}$,

$$\mathbf{M}_{o\times d} = \begin{pmatrix} m_{11} & m_{12} & \cdots & m_{1D} \\ m_{21} & m_{22} & \cdots & m_{2D} \\ \vdots & \vdots & \ddots & \vdots \\ m_{D1} & m_{D2} & \cdots & m_{DD} \end{pmatrix}$$

Each weight m_{do} reflects the contribution of migration flows from rural areas of district o to district d.[24] In the case that all migration is spread equally between all districts, each

[24]Results are robust to allowing migrants to originate from rural or urban areas.

entry in $M_{o \times d}$ will be equal to $1/d$. At the other extreme, the case in which all migration occurs within districts provides an identity matrix. Based on the data, migration patterns in India tend towards the identity matrix extreme, far from an equal distribution of migrants.

To identify the degree to which local labor demand shocks affect economic outcomes in destination sectors, I weight temperature and rainfall variation by the bilateral migration matrix, examining the migration-weighted effects of weather in district o on economic outcomes in district d through migration. The estimating equation is specified as follows,

$$Y_{dt} = \beta f(w_{dt}) + \gamma \left[\sum_{o} \frac{m_{od}}{M_d} \times f(w_{ot}) \right] + \alpha_d + \alpha_t + \phi_s t + \varepsilon_{dt}$$

where: Y_{dt} represents sectoral labor force shares in destination district d; α_d is a vector of district fixed effects; α_t is a vector of year fixed effects; $\phi_s t$ a set of state-specific time trends.

$\sum_o \frac{m_{od}}{M_d} \times f(w_{ot})$ captures the migration-weighted effects of weather in other districts.

By directly controlling for local weather effects, $f(w_{dt})$, to account for the correlation of weather across space, γ identifies the effects of weather variation in foreign districts on local labor market outcomes through migration.

Results – Migration

Table C18 presents the results of the first exercise. We observe that there is no differential effect of having a greater migrant share on the labor force share of employment. Evaluated at the mean out-migration share (6.12%), a 1°C increase in temperature is associated with a relative 1.58 percentage point increase in the labor force employed in agriculture. There is little difference between a district with no out-migrants and the average effect estimated across districts. Similar effects are estimated for other employment shares as well, suggesting that out-migration is not a driving factor in the estimated effects.

Table C19 presents the results of the second exercise. I find that the migration-weighted weather effects have no effect on employment shares in destination markets, further supporting the premise that there is little migration across districts in response to temperature increases. The estimated coefficients capture the combined effect of temperature increases from all other districts. A 1°C increase in all districts is clearly out of sample, and so a more reasonable interpretation is to consider the effect of a 1°C increase in an "average" district. The average share of total migrants from each district is 0.16 percent. The average effect of a 1°C increase in temperature on the labor force share of agriculture is a reduction of 0.01 percentage points.[25] Alternatively, we could consider the effect of a 1°C increase in temperature for a district that provides 100% of migrants. This would result in a 6.69% reduction in agricultural employment, driven by an increase in the denominator. However, this is also out-of-sample and estimates for all sectors are statistically insignificant.

The reason behind the limited migration remains unclear. Workers may face significant adjustment costs across space, or the ability of other sectors to absorb workers in response to sectoral productivity shocks may mitigate the need to move across space. Understanding the degree to which workers face spatial frictions and are therefore misallocated across space is an important area of research, but one that cannot be addressed in this paper given the transitory nature of the agricultural productivity shocks.

[25] $-0.000669 \times 0.16 = -0.000107$.

Table C18: The Moderating Effects of Out-Migration on the District Labor Force Share of Employment - By Sector

	Origin District Labor Force Shares				
	Agriculture	Manufacturing	Services	Construction	Unemployment
Daily Average Temperature (°C)	-0.0878*** (0.0234)	0.0228* (0.0120)	0.0368*** (0.0115)	0.0168 (0.0120)	-0.00502 (0.00416)
Monsoon Rainfall (100mm) (100 mm)	-0.00405 (0.00366)	0.00151 (0.00168)	-0.00122 (0.00200)	0.00259 (0.00170)	-0.0000648 (0.000471)
DAT × Migrant Share	0.00258 (0.00193)	-0.000375 (0.00125)	-0.000570 (0.000937)	-0.000938 (0.00176)	0.000381 (0.000364)
Monsoon Rainfall × Migrant Share	0.0000613 (0.000277)	-0.0000215 (0.000126)	0.000287*** (0.0000992)	-0.000296 (0.000185)	0.0000183 (0.0000294)
Fixed Effects	District, Year, 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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation 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 C19: The Effects of Weather in Foreign Districts on the Share of Employment in Destination Districts - By Sector

	Destination District Labor Force Shares				
	Agriculture	Manufacturing	Services	Construction	Unemployment
Local Daily Average Temperature (°C)	-0.0689***	0.0212**	0.0315***	0.0105	0.00569
	(0.0174)	(0.00949)	(0.0102)	(0.00650)	(0.00402)
Local Monsoon Rainfall (100 mm)	-0.00333	0.00111	0.000535	0.000661	0.00102*
	(0.00242)	(0.00123)	(0.00171)	(0.00121)	(0.000536)
Foreign Daily Average Temperature (°C)	-0.000669	9.01e-08	0.000600	-0.000131	0.000200
	(0.000811)	(0.000342)	(0.000446)	(0.000329)	(0.000160)
Foreign Monsoon Rainfall (100 mm)	-0.000924	0.000533	0.00101	-0.000551	-0.0000670
	(0.00108)	(0.000621)	(0.000780)	(0.000549)	(0.000202)
Fixed Effects	District, Year, 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: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation 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.

D The Effects of Weather on Manufacturing Firms: Supporting Evidence

D.1 ASI Data Appendix

This section provides additional details on the Annual Survey of Industries Establishment-level Microdata.

I begin by extracting a subset of variables from the raw data separately for each year and then append each year together. With this initial sample, I begin by dropping all plants that are outside of the manufacturing sector, and firms that are closed. In addition, I remove all observations with missing or zero total output data. I then combine this data with the weather data taken from the ERA-Interim Reanalysis Data archive. Finally, I drop Union Territories and then restrict the sample to be the same districts as the previous analyses.

Financial amounts are deflated to constant 2001–02 Rupees.[26] Revenue (gross sales) is deflated by a three-digit commodity price deflator available from the "Index Numbers of Wholesale Prices in India - By Groups and Sub-Groups (Yearly Averages)" produced by the Office of the Economic Adviser in the Ministry of Commerce & Industry.[27] Material inputs are deflated by constructing the average output deflator for a given industry's supplier industries based on India's 1993–94 input–output table, available from the Central Statistical Organization.

Table D1 presents descriptive statistics and differences-in-means across rigid and more flexible labor markets for regulated (columns 1-3) and unregulated (columns 4-6) firms. Across a wide-range of outcomes, there do not appear to be important differences across labor regulation environments for either regulated or unregulated firms.

[26] Thank you to Hunt Allcott, Allan Collard-Wexler, and Stephen O'Connel for publicly providing the data and code to conduct this exercise.

[27] Available from http://www.eaindustry.nic.in/

Table D1: Descriptive Statistics - Manufacturing Firms in India (2001–2007)

	Regulated Firms			Unegulated Firms		
	Rigid States	Flexible States	Difference	Rigid States	Flexible States	Difference
Total Output	1529.185	1676.697	-147.512	103.008	94.148	8.859
(Million Rs.)	(371.832)	(460.655)	(591.999)	(20.074)	(13.693)	(24.300)
Total Employment	409.741	431.264	-21.523	39.760	47.024	-7.264
(Non-mangers)	(38.865)	(65.174)	(75.883)	(2.271)	(5.252)	(6.509)
Employment	158.987	348.164	-189.177	49.386	64.705	-15.318*
(Contract Workers)	(10.299)	(138.091)	(125.979)	(1.315)	(6.681)	(8.229)
Average Day Wage	133.419	129.085	4.333	110.944	103.298	7.645
(Contract Workers)	(3.193)	(4.006)	(5.123)	(12.983)	(3.559)	(13.462)
Employment	332.317	304.044	28.272	21.263	27.269	-6.005*
(Regular Workers)	(48.374)	(17.375)	(51.400)	(1.191)	(2.869)	(3.106)
Average Day Wage	262.132	190.596	71.536	151.893	122.450	29.443
(Regular Workers)	(42.132)	(13.725)	(42.741)	(26.858)	(5.390)	(267.394)
Employment	52.999	47.555	5.447	5.253	4.735	0.517
(Managers)	(7.902)	(5.653)	(9.716)	(0.816)	(0.366)	(0.856)
Average Day Wage	852.112	728.123	123.989	561.277	448.018	113.258
(Managers)	(124.822)	(47.589)	(133.587)	(93.794)	(33.796)	(99.697)
Fixed Capital	808.488	815.740	-7.251	31.813	24.115	7.698
(Million Rs.)	(159.066)	(240.396)	(288.258)	(7.966)	(4.211)	(9.011)
Working Capital	99.282	140.489	-41.206	11.851	11.460	0.391
(Million Rs.)	(28.333)	(29.954)	(41.231)	(2.374)	(1.251)	(2.683)
Access to Electricity	0.996	0.991	0.005**	0.996	0.981	0.015**
(%)	(0.00006)	(0.002)	(0.002)	(0.002)	(0.005)	(0.006
Generates Own	0.491	0.645	-0.154***	0.163	0.379	-0.215***
Electricity (%)	(0.010)	(0.046)	(0.046)	(0.025)	(0.062)	(0.067)
Output per Worker	3.389	3.106	0.787	2.426	2.009	0.416
(Million Rs.)	(0.776)	(0.418)	(0.881)	(0.314)	(0.148)	(0.347)
log TFPR	6.040	6.037	0.002	5.402	5.429	-0.027
	(0.080)	(0.040)	(0.047)	(0.077)	(0.028)	(0.081)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the state level.

D.2 Differences-in-Temperature: Supporting Evidence

D.2.1 The IDA Doesn't Moderate the Effects of Temperature on Agricultural Outcomes

In this section I show that there are no meaningful differences in the effects of temperature on agricultural outcomes between the different labor regulation environments. This provides evidence against the premise that differences in the effects of temperature on manufacturing outcomes may be driven by differences in the intensity of the agricultural shock between labor regulation environments. Temperature does not appear to have a differential effect on agricultural yields, the value of production, or prices. By contrast, the effects of rainfall on agricultural yields and the value of production are different across labor regulation environments. There does not appear to be any effect of rainfall on agricultural production in pro-worker states. By contrast, there are meaningful effects of rainfall on agricultural production in more flexible labor regulation environments. As such, it is not possible to interpret the differential effects of rainfall shocks between labor regulation environments.

Table D2: The Moderating Effect of the Labor Regulation Environment on the Relationship between Weather and Agricultural Outcomes

	(1) Log Yield (All Crops)	(2) Log Value (All Crops)	(3) Log Price (All Crops)
Daily Average Temperature (°C)	-0.111**	-0.113**	-0.00256
	(0.0447)	(0.0401)	(0.0189)
Temperature × Flexible	-0.00977	-0.00829	0.00148
	(0.0501)	(0.0441)	(0.0277)
Monsoon Rainfall (100mm)	0.000293	-0.00219	-0.00248
	(0.00375)	(0.00640)	(0.00388)
Rainfall × Flexible	0.0139*	0.0152**	0.00126
	(0.00780)	(0.00581)	(0.00656)
Fixed Effects	Crop × District and Crop × Year		
Other Controls	Linear State-Year Time Trends		
Observations	10,275	10,275	10,275

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the state level.

D.2.2 Temperature Isn't Correlated with Amendments to the IDA

In this section I provide evidence that variation in the weather, between states or within states over time, does not appear to be correlated with the amendments made to the IDA between 1950 and 1995. This insight is robust to using both the ERA-interim reanalysis data used in the main analysis, which is only available from 1979 and to using the UDEL weather data available from 1950.

Table D3: The Effects of Temperature on Amendments to the Industrial Disputes Act

	(1) Total Change	(2) Total Change	(3) Total Change	(4) Total Change	(5) Total Change	(6) Total Change
Daily Average Temperature (°C)	-0.0236 (0.0286)	0.0292 (0.0867)	0.0354 (0.114)	-0.0324 (0.0294)	-0.0428 (0.0763)	-0.112 (0.112)
Monsoon Rainfall (100mm)	0.0267 (0.0387)	0.0000621 (0.00869)	-0.0157 (0.0233)	0.0172 (0.0171)	-0.00476 (0.0109)	0.00225 (0.0121)
District Fixed Effects	No	Yes	Yes	No	Yes	Yes
Year Fixed Effects	No	No	Yes	No	No	Yes
Observations	384	384	384	848	848	848

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. The unit of analysis is a state-year. Total Change measures the magnitude and direction of the change, e.g., if 3 pro-worker amendments were made during the year a value of 3 would be assigned to that state in that year. Standard errors are clustered at the state level.

D.3 A Simple Model of Hiring Frictions and Firm Behavior

Here I present a simple model to formalize the potential outcomes associated with the effects of hiring frictions on firm behavior, building on the model environment presented in Garicano et al., 2016.

Basic Model The model considers two types of firm, regulated and unregulated and two types of worker, unregulated (contract) workers and regulated workers. If a firm is below the regulatory threshold hiring regulated workers can result in them becoming regulated if they pass the firm-size threshold. By contrast, unregulated workers do not affect regulatory status. Above the regulatory threshold firms face *de jure* hiring costs, τ_r, when hiring regulated workers. They do not face *de jure* hiring costs when hiring unregulated workers.

First, we explore what the model predicts when there are no *de facto* hiring costs. In this situation, firms optimize over whether they are regulated or unregulated and choose the number of regulated workers accordingly.

$$\pi(\alpha) = \max_{n_u, n_r} \begin{cases} \alpha f(n_u, n_r) - w_u n_u - w_r n_r & \text{if } n_r \leq N \\ \alpha f(n_u, n_r) - w_u n_u - w_r \tau_r n_r - F & \text{if } n_r > N \end{cases}$$

$$\alpha {f_r}'(n_u, n_r) - \tilde{\tau}_r w_r = 0 \text{ with } \begin{cases} \tilde{\tau}_r = 1 & \text{if } n_r \leq N \\ \tilde{\tau}_r = \tau_r & \text{if } n_r > N \end{cases}$$

$$\alpha {f_u}'(n_u, n_r) - w_u = 0$$

$$n_r^*(\alpha, \tau_r, w_r, w_u) = {f_r}'^{-1}\left(\frac{\tilde{\tau}_r w_r}{\alpha}\right)$$

$$n_u^*(\alpha, \tau_r, w_r, w_u) = {f_u}'^{-1}\left(\frac{w_u}{\alpha}\right)$$

The model predicts that there will be differential hiring of regulated workers in labor markets with lower *de jure* hiring cost, $\frac{\partial n_r}{\partial \tau_r} < 0$. The number of unregulated workers is also a function of hiring costs τ. Under a Cobb-Douglas technology there will be differential hiring of unregulated workers in labor markets with higher *de jure* hiring costs, $\frac{\partial n_u}{\partial \tau_r} > 0$.

Incorporating *de facto* hiring costs for unregulated workers The relevance of *de facto* hiring costs, τ_u, for unregulated workers would reduce the incentive associated with hiring unregulated workers in markets with greater *de jure* hiring costs.

$$\pi(\alpha) = \max_{n_u, n_r} \begin{cases} \alpha f(n_u, n_r) - w_u n_u - w_r n_r & \text{if } n_r \leq N \\ \alpha f(n_u, n_r) - w_u \tau_u n_u - w_r \tau_r n_r - F & \text{if } n_r > N \end{cases}$$

$$\alpha {f_r}'(n_u, n_r) - \tilde{\tau}_r w_r = 0 \text{ with } \begin{cases} \tilde{\tau}_r = 1 & \text{if } n_r \leq N \\ \tilde{\tau}_r = \tau_r & \text{if } n_r > N \end{cases}$$

$$\alpha {f_u}'(n_u, n_r) - \tilde{\tau}_u w_u = 0 \text{ with } \begin{cases} \tilde{\tau}_u = 1 & \text{if } n_r \leq N \\ \tilde{\tau}_u = \tau_u & \text{if } n_r > N \end{cases}$$

$$n_r^*(\alpha, \tau_r, w_r, \tilde{\tau}_u, w_u) = {f_r}'^{-1}\left(\frac{\tilde{\tau}_r w_r}{\alpha}\right)$$

$$n_u^*(\alpha, \tilde{\tau}_r, w_r, \tilde{\tau}_u, w_u) = {f_u}'^{-1}\left(\frac{\tilde{\tau}_u w_u}{\alpha}\right)$$

As before, the model predicts that there will be differential hiring of regulated workers in labor markets with lower *de jure* hiring cost, $\frac{\partial n_r}{\partial \tau_r} < 0$. The number of unregulated workers is decreasing in *de facto* hiring costs, $\frac{\partial n_u}{\partial \tau_u} < 0$. To the degree that *de facto* hiring costs are higher in labor markets with higher *de jure* hiring costs, $rho(\tau_r, \tau_u) > 0$, as it is argued to be in the context of the IDA, the incentive to hire unregulated workers as a substitute is diminished. When *de facto* hiring costs for unregulated workers are empirically relevant we may see differential hiring of unregulated workers in labor markets with lower *de facto* hiring costs. The overall effect depends on the relative importance of *de facto* vs. *de jure* hiring costs.

Considering regulated workers as a fixed factor in the short run The discussion so far considers equilibrium hiring decisions. Firms choose the optimal number of regulated and unregulated workers, subject to *de jure* and *de facto* hiring costs, and choose whether to be regulated or unregulated firms, subject to the indifference condition,

$$\alpha f(N, n_u) - w_r N - w n_u = \alpha f(n_r^*(\alpha), n_u^*(\alpha)) - w_u \tau_u n_u^*(\alpha) - w_r \tau_r n_r^*(\alpha) - F$$

In the empirical analysis we explore the effects of transitory labor supply shocks on firm hiring decisions. It is plausible to think that in markets where hiring costs are more binding, the number of regulated workers might be fixed in the short run. We would not expect firms to change their regulatory status, or change the number of regulated workers in response to short-run shocks.

If we consider regulated workers to be a fixed factor of production in the short run, when $\tau_r > 1$, the insight gained from introducing *de facto* hiring costs become unambiguous.

This is because the hiring of unregulated workers no longer depends on the the number of regulated workers, and consequently does not depend on *de jure* hiring costs,

$$n_u^*(\alpha, \tilde{\tau}_u, w_u) = {f_u}'^{-1}\left(\frac{\tilde{\tau}_u w_u}{\alpha}\right) \text{ with } \begin{cases} \tilde{\tau}_u = 1 & \text{if } \bar{n}_r \leq N \\ \tilde{\tau}_u = \tau_u & \text{if } \bar{n}_r > N \end{cases}$$

In this case there is an unambiguous differential increase in the hiring of unregulated workers in markets with lower *de facto* hiring costs, $\frac{\partial n_u}{\partial \tau_u} < 0$. If *de facto* hiring costs are not empirically relevant, $\tau_u = 0$ we would not expect any differential increase in the hiring of unregulated workers.

Overview of Theoretical Predictions Table D4 presents an overview of the predicted hiring responses of regulated firms under the different model assumptions. The empirical relevance of *de facto* hiring costs is identified if a relative increase in the employment of unregulated contract workers is estimated in flexible labor markets ($\Theta(\tau_u > 0, \frac{\partial n_r}{\partial temperature} > 0)$ and $\Theta(\tau_u > 0, \frac{\partial n_r}{\partial temperature} = 0)$). The empirical relevance of *de facto* hiring costs is also identified if there is no relative increase in unregulated contract workers and a relative increase in the number of regulated workers in more flexible labor markets ($\Theta(\tau_u > 0, \frac{\partial n_r}{\partial temperature} > 0)$). The absence of *de facto* hiring costs would be identified if I estimated no relative increase in the employment of unregulated contract workers and no increase in the employment of regulated workers ($\Theta(\tau_u, \frac{\partial n_r}{\partial temperature} = 0)$.) The only case that does not allow us to say anything about the empirical relevance of *de facto* hiring costs is if there is a relative increase in the number of unregulated workers in rigid labor markets and a relative increase in the number of regulated workers in flexible labor markets ($\Theta(\tau_u = 0, \frac{\partial n_r}{\partial temperature} > 0)$ vs. $\Theta(\tau_u > 0, \frac{\partial n_r}{\partial temperature} > 0)$). This could arise if *de facto* costs are empirically relevant, but are less important for the hiring of unregulated workers than *de jure* hiring costs, or if *de facto* hiring costs are not empirically relevant. Nevertheless, in this setting we still identify a relative increase in the employment of (regulated) workers in more flexible labor markets, allowing us to identify the labor reallocation effect separately from the the residual effects of temperature on manufacturing outcomes.

Table D4: An Overview of Empirical Predictions for Regulated Firms under Different Model Assumptions

Model	Predicted Hiring Responses for Regulated Firms	
Assumptions	Unregulated Contract Workers	Regulated Workers
$\Theta(\tau_u = 0, \frac{\partial n_r}{\partial temperature} > 0)$	$0 < \frac{\partial n_{u,Flexible}}{\partial temperature} < \frac{\partial n_{u,Rigid}}{\partial temperature}$	$0 < \frac{\partial n_{r,Rigid}}{\partial temperature} < \frac{\partial n_{r,Flexible}}{\partial temperature}$
$\Theta(\tau_u = 0, \frac{\partial n_r}{\partial temperature} = 0)$	$0 < \frac{\partial n_{u,Rigid}}{\partial temperature} = \frac{\partial n_{u,Flexible}}{\partial temperature}$	$0 = \frac{\partial n_{r,Rigid}}{\partial temperature} = \frac{\partial n_{r,Flexible}}{\partial temperature}$
$\Theta(\tau_u > 0, \frac{\partial n_r}{\partial temperature} > 0)$	$0 < \frac{\partial n_{u,Rigid}}{\partial temperature} \lesseqgtr \frac{\partial n_{u,Flexible}}{\partial temperature}$	$0 < \frac{\partial n_{r,Rigid}}{\partial temperature} < \frac{\partial n_{r,Flexible}}{\partial temperature}$
$\Theta(\tau_u > 0, \frac{\partial n_r}{\partial temperature} = 0)$	$0 < \frac{\partial n_{u,Rigid}}{\partial temperature} < \frac{\partial n_{u,Flexible}}{\partial temperature}$	$0 = \frac{\partial n_{r,Rigid}}{\partial temperature} = \frac{\partial n_{r,Flexible}}{\partial temperature}$

D.4 Wage Gaps Between Agriculture and Manufacturing

In this section I explore the common support between agricultural workers and workers in manufacturing, using worker-level data from the NSS. I estimate worker-level mincerian wage regressions to estimate the size of wage gaps after controlling for education, age, gender, district and year fixed effects. Table D5 shows that there is a significant wage gap between permanent manufacturing workers and agricultural workers, with permanent manufacturing workers earning 1.4 times more than agricultural workers within local labor markets after controlling for individual characteristics.[28] We observe that the average wage gap between casual manufacturing workers and agricultural workers is far smaller after controlling for individual characteristics, with casual manufacturing workers earning 1.1 times more than agricultural workers, a difference that is statistically significant at the 10% level. There is likely to be greater common support between the wages of contract workers and agricultural workers, consistent with the premise that workers within low-skill groups are relatively substitutable across sectors. This suggests that labor markets in this context may not be dualistic across sectors per se (agriculture vs. non-agriculture), but rather can be characterized as dualistic across types of activities or skill. The fact that non-agricultural sectors tend to have a distribution of workers with a higher dispersion of skill likely conflates the interpretation of a dualistic labor market across sectors. A sectoral dimension may become more important as workers rise up the skill ladder and work in more specialized tasks, reducing the substitutability of workers across sectors.

Table D5: Average Wage Gap (Agriculture vs. Manufacturing)

	India Wide	Within District	Within District Skill Adjusted
Average Wage Gap (Casual Manufacturing Workers)	1.352***	1.163***	1.106**
Average Wage Gap (Regular Manufacturing Workers)	2.295***	2.016***	1.397***
Average Day Wage in Agriculture (Rs.)	49.819	49.819	49.819
Year Fixed Effects	Yes	Yes	Yes
District Fixed Effects	No	Yes	Yes
Individual Controls	No	No	Yes
Observations	68,940	68,940	68,940

f

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Individual level controls include age, education, sex, and whether an individual lives in a rural area. Estimates are based on individual-level mincerian wage regressions on the working-age population (14-65) controlling for a sector dummy (β) specifying whether the individual is engaged in agricultural, casual manufacturing, or regular manufacturing employment. The wage gap is calculated as $\exp(\beta)$.

[28] This data does not make a distinction between the informal and formal sector.

D.5 Labor Reallocation into the Informal Manufacturing Sector

In this section I explore the degree to which temperature-driven labor reallocation occurs in the informal manufacturing sector. I collected data from the NSSO Unorganized Manufacturing Survey for 2005 and 2010. I extract data on the number of workers and total output in each informal establishments. I construct a sample-weighted aggregate of the number of informal sector manufacturing workers and output in each district-year. Given the limited panel the estimates of this exercise should be interpreted with caution.

I regress the log number of workers and log output on temperature and rainfall, controlling for district and year fixed effects as well as state-year time trends, following the same specification as section 3,

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

The results of this exercise are presented in Table D6. I estimate that a 1°C increase in temperature is associated with a 12% increase in the number of informal sector manufacturing workers and a 33% increase in output, however, the estimates are statistically insignificant at conventional levels. Given limited data availability, it is possible that this exercise is underpowered. Nevertheless, the magnitude of these estimates are substantial suggesting that the informal sector could absorbs a substantial share of the estimated labor reallocation. Consistent with estimates in the other sections of this paper I estimate small, statistically insignificant, effects of rainfall on informal sector employment.

Table D6: The Effects of Weather on Informal Manufacturing Sector Employment and Output

	(1) log Workers	(2) log Output
Daily Average Temperature (°C)	0.121 (0.0910)	0.330 (0.257)
Monsoon Rainfall (100mm)	-0.00239 (0.0168)	-0.0212 (0.0354)
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
State-Year Time Trends	Yes	Yes
Observations	604	604

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modeled in Conley (1999) and serial correlation 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.

D.6 Differences-in-Temperature: Additional Results

D.6.1 Alternative Codifications of Exposure to the Industrial Disputes Act

In this section I explore the robustness of the main results to alternative codifications of the Industrial Disputes Act measure. Given that there are no differences in the effects of temperature on manufacturing outcomes across labor regulation environments for unregulated firms I restrict attention to regulated firms. The baseline estimates restricted to regulated firms are presented in Panel A of Table D7. This measure uses pro-worker states as the baseline category and defines FLEXIBLE as neutral and pro-employer States. In Panel B I incorporate a separate category for Neutral and Pro-Employer states, defining an ordinal ranking, following Besley and Burgess (2004). For comparability with the main results, pro-Worker states are coded as zero, neutral states are coded as 0.5 and pro-employer states are coded as 1. The estimated effects are similar to the baseline results. In Panel C I construct a cardinal ranking, allowing pro-worker and pro-employer states to vary in the intensity of their classification. West Bengal is coded as the most pro-worker state with a value of -4, followed by Maharashtra (-2), and Odisha (-1). Tamil Nadu and Andhra Pradesh are coded as the most pro-employer states with a value of 2, followed by Rajasthan, Karnataka, and Kerala, coded as 1. For comparability with the main results, I normalize the coding to be between 0 and 1, with West Bengal coded as zero and Tamil Nadu and Andhra Pradesh coded as 1. These estimates are qualitatively similar. The magnitude of the estimated effects are larger than the baseline estimates. Finally, in Panel D I include separate interaction terms for Neutral and Pro-Employer states. There is no difference in the effects of temperature in neutral and flexible states motivating the combination of these categories in the main specification.

Table D7: Alternative Codifications of the Labor Regulation Environment

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Panel A: Baseline					
Daily Average Temperature (°C)	-0.173***	-0.193***	-0.0672	-0.00497	-0.0690***
	(0.0199)	(0.0480)	(0.0705)	(0.0121)	(0.00691)
Temperature × Flexible	0.136***	0.152**	0.0402	-0.0464*	0.0716***
	(0.0260)	(0.0528)	(0.0648)	(0.0228)	(0.0228)
Panel B: Ordinal Ranking					
Daily Average Temperature (°C)	-0.138***	-0.165***	-0.0474	-0.00482	-0.0405
	(0.0406)	(0.0373)	(0.0635)	(0.0203)	(0.0277)
Temperature × Flexible	0.132**	0.180***	0.0167	-0.0747***	0.0474
	(0.0571)	(0.0519)	(0.0835)	(0.0235)	(0.0282)
Panel C: Cardinal Ranking					
Daily Average Temperature (°C)	-0.214***	-0.283***	-0.0294	0.0216	-0.0705**
	(0.0353)	(0.0462)	(0.101)	(0.0324)	(0.0261)
Temperature × Flexible	0.235***	0.338***	-0.0177	-0.101*	0.0894*
	(0.0460)	(0.0781)	(0.131)	(0.0558)	(0.0443)
Panel D: Separate Categories					
Daily Average Temperature (°C)	-0.173***	-0.192***	-0.0663	-0.00652	-0.0703***
	(0.0200)	(0.0486)	(0.0710)	(0.0110)	(0.00670)
Temperature × Neutral	0.144***	0.145**	0.0520	-0.0341	0.0896***
	(0.0362)	(0.0589)	(0.0667)	(0.0254)	(0.0281)
Temperature × Flexible	0.114***	0.158***	-0.00626	-0.0782**	0.0376**
	(0.0362)	(0.0541)	(0.0657)	(0.0289)	(0.0132)
Fixed Effects	Sector × District & Sector × Year				
Other Controls	Monsoon Rainfall (inc. interactions) & Linear State × Year Time Trends				
Observations	36,160	14,357	36,160	14,357	36,160

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. 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).

D.6.2 Weighted Results

In this section I present results documenting robustness of the main results to the use of sampling weights. The results are qualitatively and quantitatively similar to the unweighted results. Furthermore, I do not reject the null hypothesis that there is no differential effect of temperature across labor regulation environments for unregulated firms – an important test for the research design.

Table D8: The Differential Effects of Temperature by Regulatory Status (Weighted)

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Regression Estimates					
Daily Average Temperature (°C): γ_1	-0.108 (0.0699)	-0.262*** (0.0661)	-0.0519 (0.0432)	0.0103 (0.0177)	-0.0216 (0.0129)
Temperature $\times$ Flexible: γ_2	0.110 (0.0700)	0.249** (0.0967)	0.0598 (0.0429)	-0.0625* (0.0312)	0.0442* (0.0248)
Temperature $\times$ Below Threshold: γ_3	0.118** (0.0546)	0.151 (0.109)	0.0601 (0.0388)	0.0342 (0.0345)	0.0169 (0.0193)
Temperature $\times$ Flexible $\times$ Below Threshold: γ_4	-0.176*** (0.0498)	-0.305** (0.119)	-0.0801* (0.0407)	0.00876 (0.0364)	-0.0224 (0.0330)
Fixed Effects	Sector $\times$ District $\times$ Regulatory Group and Sector $\times$ Year $\times$ Regulatory Group				
Other Controls	Monsoon Rainfall (including interactions) and Linear State $\times$ Year Time Trends				
Observations	88,846	31,051	88,846	31,051	88,846
Formal Tests					
Difference Above Threshold: $H_0 : \gamma_2 = 0$	0.110 (0.0700)	0.249** (0.0967)	0.0598 (0.0429)	-0.0625* (0.0312)	0.0442* (0.0248)
Difference Below Threshold: $H_0 : \gamma_2 + \gamma_4 = 0$	-0.065 (0.048)	-0.056 (0.083)	-0.020 (0.018)	-0.053 (0.038)	0.021 (0.016)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Regressions are weighted using sampling weights provided by the Central Statistics Office. "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. District $\times$ Sector and Sector $\times$ 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).

Table D9: The Differential Effects of Temperature by Regulatory Status (Weather × Sector Controls)

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Regression Estimates					
Daily Average Temperature (°C): γ_1	-0.0620 (0.0866)	-0.133* (0.0641)	-0.0360 (0.0595)	-0.00790 (0.0259)	-0.0652*** (0.0186)
Temperature × Flexible: γ_2	0.0954** (0.0394)	0.162** (0.0641)	0.0338 (0.0557)	-0.0533* (0.0278)	0.0626*** (0.0207)
Temperature × Below Threshold: γ_3	0.155*** (0.0334)	0.182* (0.0962)	0.109 (0.0673)	0.00764 (0.0363)	0.0569*** (0.0139)
Temperature × Flexible × Below Threshold: γ_4	-0.0927** (0.0403)	-0.273** (0.124)	-0.0864 (0.0721)	0.0443 (0.0377)	-0.0431 (0.0253)
Fixed Effects	Sector × District × Regulatory Group and Sector × Year × Regulatory Group				
Other Controls	Monsoon Rainfall (including interactions), Linear State × Year Time Trends, and Weather × Sector Dummy Variable Controls				
Observations	88,846	31,051	88,846	31,051	88,846
Formal Tests					
Difference Above Threshold $H_0 : \gamma_2 = 0$	0.0954** (0.0394)	0.162** (0.0641)	0.0338 (0.0557)	-0.0533* (0.0278)	0.0626*** (0.0207)
Difference Below Threshold: $H_0 : \gamma_2 + \gamma_4 = 0$	0.002 (0.045)	-0.111 (0.113)	-0.053 (0.031)	-0.009 (0.037)	0.019 (0.013)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Regressions are weighted using sampling weights provided by the Central Statistics Office. "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. 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).

Table D10: The Differential Effects of Temperature by Regulatory Status (Weather × Rural Controls)

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Regression Estimates					
Daily Average Temperature (°C): γ_1	-0.120***	-0.155***	-0.0532	0.00571	-0.0575***
	(0.0234)	(0.0462)	(0.0705)	(0.0106)	(0.00786)
Temperature × Flexible: γ_2	0.102**	0.146**	0.0390	-0.0595**	0.0617**
	(0.0360)	(0.0599)	(0.0651)	(0.0265)	(0.0222)
Temperature × Below Threshold: γ_3	0.146***	0.180*	0.0998	0.00991	0.0545***
	(0.0317)	(0.0977)	(0.0737)	(0.0379)	(0.0135)
Temperature × Flexible × Below Threshold: γ_4	-0.0946**	-0.268**	-0.0841	0.0472	-0.0395
	(0.0412)	(0.119)	(0.0778)	(0.0401)	(0.0268)
Fixed Effects	Sector × District × Regulatory Group and Sector × Year × Regulatory Group				
Other Controls	Monsoon Rainfall (including interactions), Linear State × Year Time Trends, Weather × Rural, and Rural Controls				
Observations	88,846	31,051	88,846	31,051	88,846
Formal Tests					
Difference Above Threshold $H_0 : \gamma_2 = 0$	0.102**	0.146**	0.0390	-0.0595**	0.0617**
	(0.0360)	(0.0599)	(0.0651)	(0.0265)	(0.0222)
Difference Below Threshold: $H_0 : \gamma_2 + \gamma_4 = 0$	0.007	-0.122	-0.045	-0.012	0.022
	(0.041)	(0.111)	(0.033)	(0.036)	(0.015)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Regressions are weighted using sampling weights provided by the Central Statistics Office. "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. 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).

Table D11: The Differential Effects of Temperature by Regulatory Status (Weather × Privately Owned Firm Controls)

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Regression Estimates					
Daily Average Temperature (°C): γ_1	-0.138*** (0.0247)	-0.133** (0.0467)	-0.0839 (0.0711)	0.00629 (0.0114)	-0.0895*** (0.00938)
Temperature × Flexible: γ_2	0.121*** (0.0334)	0.141** (0.0604)	0.0685 (0.0668)	-0.0579** (0.0266)	0.0951*** (0.0213)
Temperature × Below Threshold: γ_3	0.166*** (0.0323)	0.179* (0.0995)	0.118 (0.0749)	0.0133 (0.0363)	0.0766*** (0.0133)
Temperature × Flexible × Below Threshold: γ_4	-0.121*** (0.0404)	-0.269** (0.123)	-0.110 (0.0780)	0.0409 (0.0382)	-0.0695** (0.0265)
Fixed Effects	Sector × District × Regulatory Group and Sector × Year × Regulatory Group				
Other Controls	Monsoon Rainfall (including interactions), Linear State × Year Time Trends, Weather × Private Ownership, and Private Ownership Controls				
Observations	88,846	31,051	88,846	31,051	88,846
Formal Tests					
Difference Above Threshold $H_0 : \gamma_2 = 0$	0.121*** (0.0334)	0.141** (0.0604)	0.0685 (0.0668)	-0.0579** (0.0266)	0.0951*** (0.0213)
Difference Below Threshold: $H_0 : \gamma_2 + \gamma_4 = 0$	0.001 (0.042)	-0.128 (0.112)	-0.041 (0.031)	-0.017 (0.036)	0.026 (0.016)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Regressions are weighted using sampling weights provided by the Central Statistics Office. "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. 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).

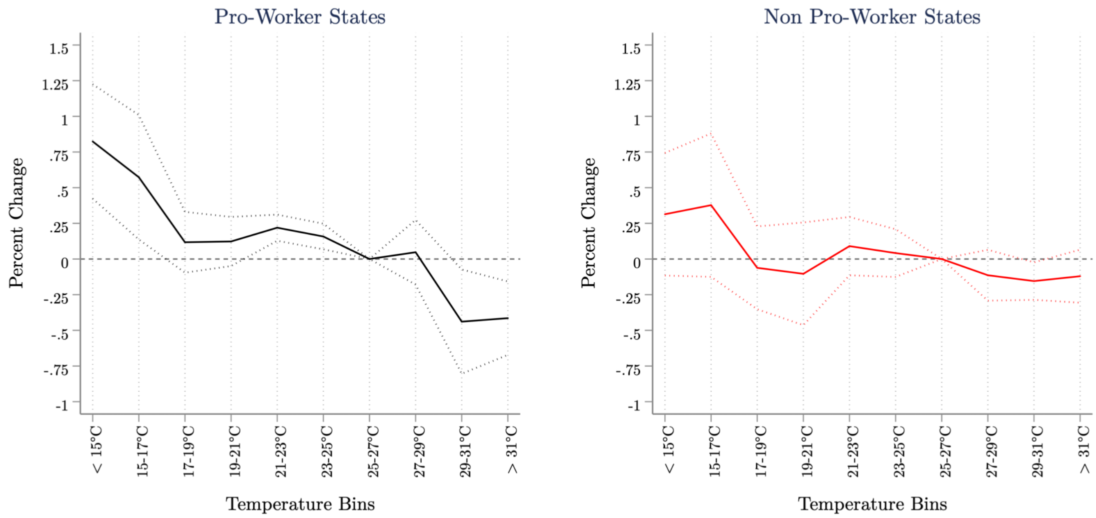
D.6.3 Non-Linearities in the Temperature Schedule

Table D12: The Differential Effects of Temperature by Regulatory Status (Degree-Days)

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Degree Days (10 days) $t_L = 17, t_H = \infty$	-0.00610***	-0.00490***	-0.00290	-0.000722	-0.00257***
	(0.00152)	(0.00124)	(0.00204)	(0.000558)	(0.000500)
DD High × Flexible	0.00481***	0.00520***	0.00186	0.000144	0.00218***
	(0.00128)	(0.00172)	(0.00179)	(0.000550)	(0.000631)
Degree Days (10 days) $t_L = 0, t_H = 17$	-0.00161	-0.00429	0.000359	0.00156*	-0.000155
	(0.00224)	(0.00578)	(0.00102)	(0.000864)	(0.000934)
DD Low × Flexible	0.00109	0.000227	-0.000606	-0.00446**	0.000953
	(0.00312)	(0.00621)	(0.00169)	(0.00161)	(0.00125)
Fixed Effects	Sector × District & Sector × Year				
Other Controls	Monsoon Rainfall (inc. interactions) & Linear State × Year Time Trends				
Observations	36,160	14,357	36,160	14,357	36,160

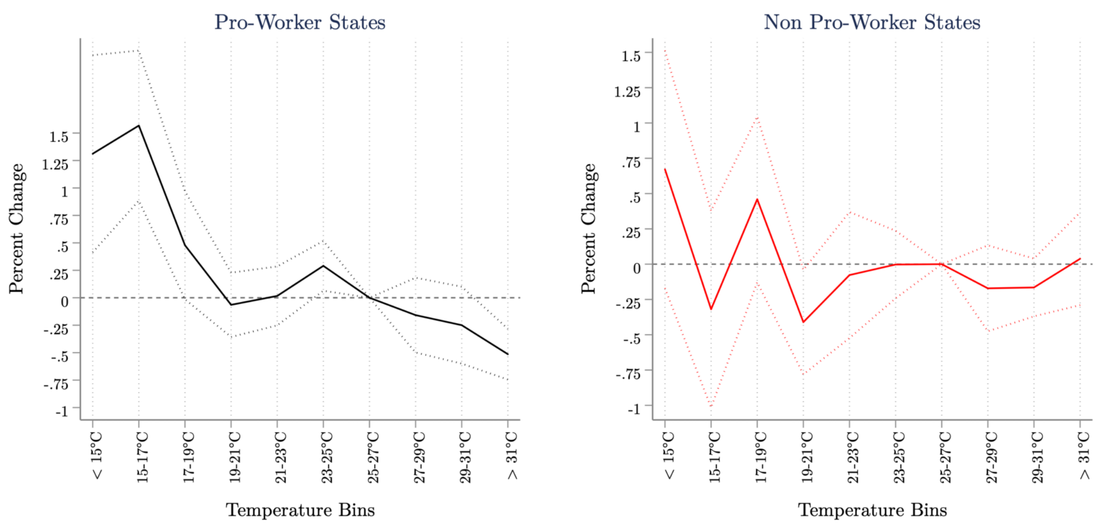
Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are clustered at the state level as this is the level at which the labor regulation policy varies. Results are robust to accounting for broader spatial correlations as modeled in Conley (1999) and serial correlation as modeled in Newey and West (1987).

Figure D1: The Differential Effect of Temperature on Total Output



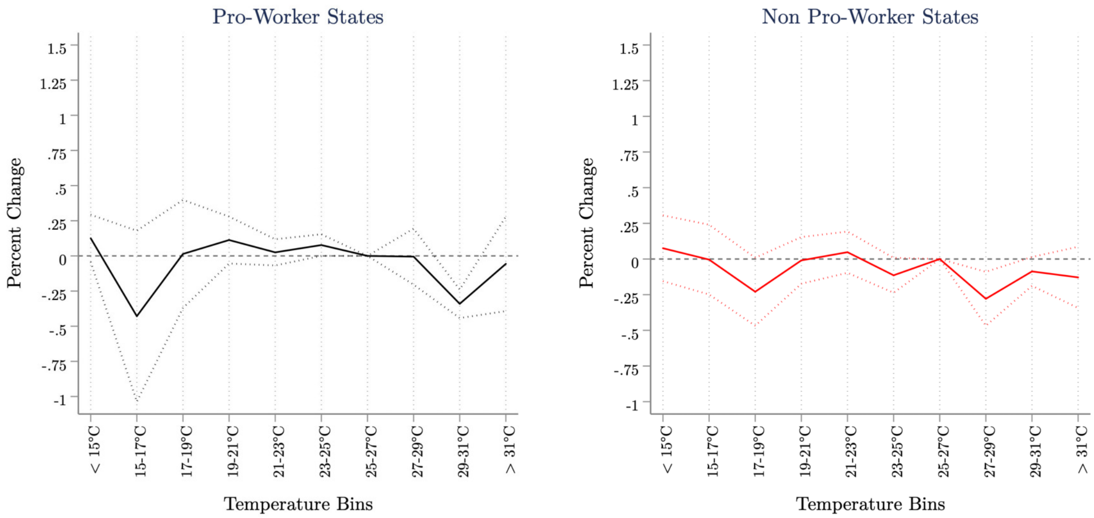
Notes: Standard errors are clustered at the state level.

Figure D2: The Differential Effect of Temperature on the Number of Contract Workers



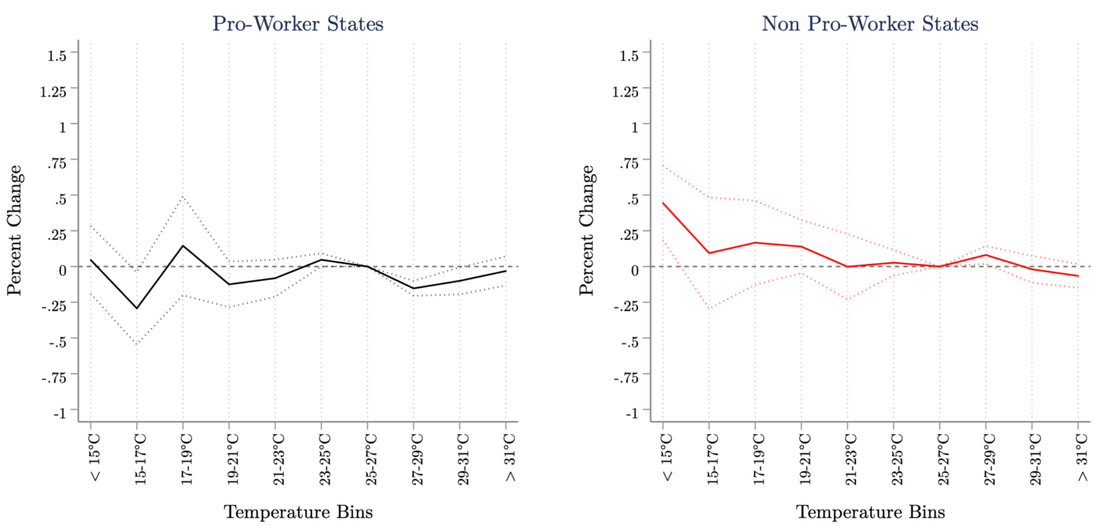
Notes: Standard errors are clustered at the state level.

Figure D3: The Differential Effect of Temperature on the Number of Regular Workers



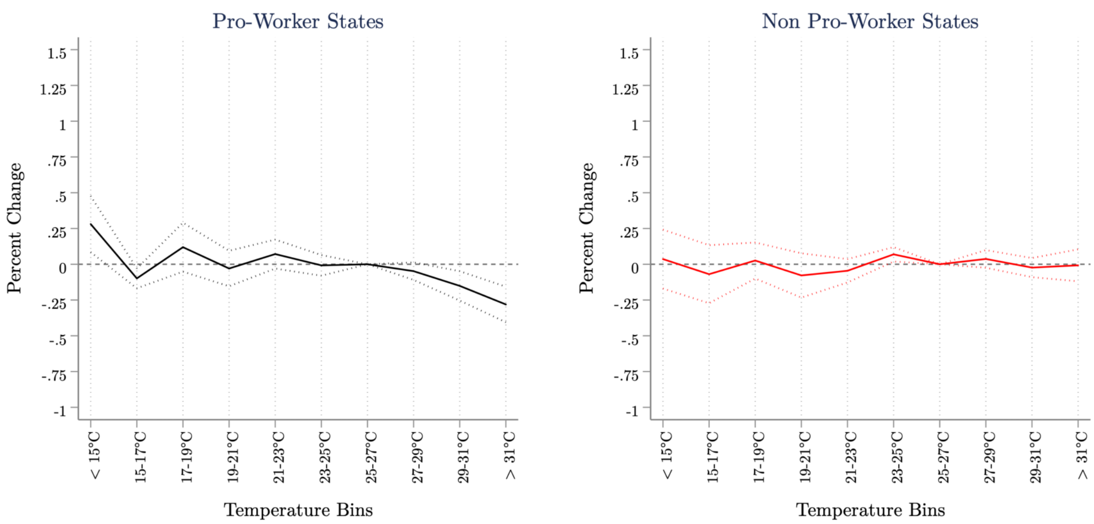
Notes: Standard errors are clustered at the state level.

Figure D4: The Differential Effect of Temperature on the Average Contract Worker Wage



Notes: Standard errors are clustered at the state level.

Figure D5: The Differential Effect of Temperature on the Average Regular Worker Wage



Notes: Standard errors are clustered at the state level.

D.6.4 Lags and Leads

Table D13: Controlling for Temperature and Rainfall Lags and Leads

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Daily Average Temperature (°C)	-0.173***	-0.193***	-0.0672	-0.00497	-0.0690***
	(0.0199)	(0.0480)	(0.0705)	(0.0121)	(0.00691)
Temperature × Flexible	0.136***	0.152**	0.0402	-0.0464*	0.0716***
	(0.0260)	(0.0528)	(0.0648)	(0.0228)	(0.0228)
1-year Lag	No	No	No	No	No
1-year Lead	No	No	No	No	No
Daily Average Temperature (°C)	-0.171***	-0.159***	-0.0646	0.0000346	-0.0612***
	(0.0233)	(0.0536)	(0.0469)	(0.0134)	(0.00919)
Temperature × Flexible	0.136***	0.136**	0.0340	-0.0616***	0.0642***
	(0.0334)	(0.0608)	(0.0471)	(0.0196)	(0.0207)
1-year Lag	Yes	Yes	Yes	Yes	Yes
1-year Lead	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District & Sector × Year				
Other Controls	Monsoon Rainfall (inc. interactions) & Linear State × Year Time Trends				
Observations	36,160	14,357	36,160	14,357	36,160

Notes: Panel A reports baseline estimates without lag and lead controls for rainfall and temperature. Panel B reports estimates that include lag and lead controls for rainfall and temperature. Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. 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).

D.6.5 The Relative Importance of Temperature vs. Rainfall for Manufacturing Outcomes in India

In this section I explore the relative importance of temperature over rainfall, as explored in other sections. This exercise provides little additional insight as the concern, as with temperature, is that rainfall could have direct effects on manufacturing other than through temperature. For example, rainfall affects electricity provision through hydroelectric dams. Nevertheless, there is still value in reporting the estimates on rainfall, evaluating how they change when controlling for temperature, and exploring the robustness of the findings to alternative weather data sets. The results of this analysis are presented in Table D14 and Table D15

In Table D14 I present results using the main weather data, the ERA-Interim Reanalysis data. In Panel A, I present the baseline results for regulated firms as a comparison. In Panel B, I show that the estimated effects are qualitatively and quantitatively similar when rainfall and its interaction with the labor regulation environment measure are not included. This suggests that rainfall is not strongly correlated with manufacturing outcomes. Consistent with this Panels C and D present estimates for monsoon rainfall. Panel C includes controls for temperature. Panel D does not control for temperature. In both cases rainfall has no meaningful effects on firm outcomes. Table D15 replicates the above analysis using the UDEL weather data.

Table D14: The Relative Importance of Temperature vs. Rainfall for Manufacturing Outcomes

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Panel A: Temperature (Controlling for Rainfall)					
Daily Average Temperature (°C)	-0.173***	-0.193***	-0.0672	-0.00497	-0.0690***
	(0.0199)	(0.0480)	(0.0705)	(0.0121)	(0.00691)
Temperature × Flexible	0.136***	0.152**	0.0402	-0.0464*	0.0716***
	(0.0260)	(0.0528)	(0.0648)	(0.0228)	(0.0228)
Panel B: Temperature (No Rainfall Controls)					
Daily Average Temperature (°C)	-0.114***	-0.152**	-0.0528	0.0217	-0.0498***
	(0.0217)	(0.0604)	(0.0549)	(0.0188)	(0.00796)
Temperature × Flexible	0.0914***	0.131**	0.0200	-0.0545**	0.0534***
	(0.0271)	(0.0586)	(0.0520)	(0.0243)	(0.0181)
Panel C: Rainfall (Controlling for Temperature)					
Monsoon Rainfall (100mm)	-0.0180***	-0.0130	-0.00478	-0.00814	-0.00606***
	(0.00619)	(0.00959)	(0.00702)	(0.00579)	(0.000833)
Rainfall × Flexible	0.0135**	0.00487	0.00652	0.000870	0.00569*
	(0.00563)	(0.0110)	(0.00671)	(0.00640)	(0.00271)
Panel D: Rainfall (No Temperature Controls)					
Monsoon Rainfall (100mm)	-0.00745	0.00217	-0.000706	-0.00803	-0.00178**
	(0.00538)	(0.0128)	(0.00262)	(0.00552)	(0.000637)
Rainfall × Flexible	0.00564	-0.00635	0.00424	0.00440	0.00142
	(0.00517)	(0.0131)	(0.00330)	(0.00589)	(0.00196)
Fixed Effects	Sector × District & Sector × Year				
Other Controls	Monsoon Rainfall (inc. interactions) & Linear State × Year Time Trends				
Observations	36,160	14,357	36,160	14,357	36,160

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. 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).

Table D15: The Relative Importance of Temperature vs. Rainfall for Manufacturing Outcomes (UDEL)

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Panel A: Temperature (Controlling for Rainfall)					
Daily Average Temperature (°C)	-0.115	-0.112	-0.0869	-0.0142	-0.0640***
	(0.0811)	(0.0730)	(0.0746)	(0.0186)	(0.00945)
Temperature × Flexible	0.0497	0.120*	0.0612	-0.0555***	0.0458***
	(0.0807)	(0.0634)	(0.0693)	(0.0181)	(0.0125)
Panel B: Temperature (No Rainfall Controls)					
Daily Average Temperature (°C)	-0.0664**	-0.199**	-0.0147	0.00214	-0.0428***
	(0.0298)	(0.0765)	(0.0723)	(0.0179)	(0.0125)
Temperature × Flexible	0.0235	0.189***	-0.0204	-0.0658***	0.0279**
	(0.0368)	(0.0636)	(0.0698)	(0.0160)	(0.0129)
Panel C: Rainfall (Controlling for Temperature)					
Monsoon Rainfall (100mm)	-0.0104	0.0161***	-0.0137***	-0.00324**	-0.00429*
	(0.0125)	(0.00303)	(0.00163)	(0.00134)	(0.00215)
Rainfall × Flexible	0.00340	-0.0117*	0.0178***	0.00133	0.00342
	(0.0125)	(0.00563)	(0.00188)	(0.00191)	(0.00230)
Panel D: Rainfall (No Temperature Controls)					
Monsoon Rainfall (100mm)	-0.00440	0.0223***	-0.00911**	-0.00244	-0.000905
	(0.00867)	(0.00529)	(0.00374)	(0.00143)	(0.00227)
Rainfall × Flexible	-0.000230	-0.0190***	0.0140***	0.00369**	0.000558
	(0.00834)	(0.00527)	(0.00430)	(0.00164)	(0.00207)
Fixed Effects	Sector × District and Sector × Year				
Other Controls	Monsoon Rainfall (inc. interactions) & Linear State × Year Time Trends				
Observations	36,160	14,357	36,160	14,357	36,160

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. 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).

D.6.6 Productivity Results

Basic Estimation The following provides an explicit model of TFPR, in the context of a profit-maximizing firm.

Each firm i, in time t, produces output Q_{it} using the following (industry-specific) technology:

$$Q_{it} = A_{it} K_{it}^{\alpha_k} M_{it}^{\alpha_m} L_{it}^{\alpha_L}$$

where K_{it} is the capital input, L_{it} is the labor input, and M_{it} is the materials input. Furthermore, I assume constant returns to scale in production so $\alpha_M + \alpha_K + \alpha_L = 1$.

The demand curve for the firm's product has a constant elasticity:

$$Q_{it} = B_{it} P_{it}^{-\epsilon}$$

Combining these two equations, I obtain an expression for the sales-generating production function:

$$S_{it} = \Omega_{it} K_{it}^{\beta_k} M_{it}^{\beta_M} L_{it}^{\beta_L}$$

where $\Omega_{it}(true) = A_{it}^{1-\frac{1}{\epsilon}} B_{it}^{\frac{1}{\epsilon}}$, and $\beta_X = \alpha_X(1 - \frac{1}{\epsilon})$ for $X \in \{K, L, M\}$. Within the confines of this paper, I define true productivity as $\omega_{it} \equiv \log(\Omega_{it})$.

To recover a measure of ω_{it}, I compute the value of $\beta_L, and \beta_M$ using median regression for each industry-year cell.

$$\beta_X = median\left(\left\{\frac{P_{it}^X X_{it}}{S_{it}}\right\}\right) \qquad \text{for } X \in \{L, M\}$$

To recover the coefficient on capital, β_K, I use the assumption of constant returns to scale in production, i.e., $\sum_X \alpha_X = 1$, such that:

$$\beta_K = \frac{\epsilon - 1}{\epsilon} - \beta_L - \beta_M$$

For ease of measurement I set ϵ to be constant for all firms. Following Bloom (2009) I set $\epsilon = 4$. Using these estimates I compute ω_{it},

$$\omega_{it}(est) = \log(S_{it}) - \beta_K \log(K_{it}) - \beta_M \log(M_{it}) - \beta_L \log(L_{it})$$

Allowing for Differences in the Elasticity of Substitution Within Labor As suggested by the empirical results, contract labor does not appear to be perfectly substitutable with regular labor as is implied under the Cobb-Douglas production function. This section presents an alternative production function to estimate productivity, allowing for imperfect substitutability between these two labor types. Specifically, I estimate a nested Cobb-Douglas production function, in which the aggregate labor factor is a CES function of contract and regular workers.

As above, the top-level sales-generating production function is Cobb-Douglas,

$$S_{it} = \Omega_{it} K_{it}^{\beta_k} M_{it}^{\beta_M} L_{it}^{\beta_L}$$

However, the Labor input is CES, i.e.,

$$L_{it} = [\theta_c L_{cit}^{\frac{\sigma-1}{\sigma}} + \theta_p L_{pit}^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}}$$

In the event that contract workers and regular workers are perfectly substitutable, this production function collapses back to the standard Cobb-Douglas production function. Given the results presented in the main text, each of the parameters in the CES structure are observed or estimated $\theta_c L_{cit} = \bar{w}_{cit} L_{cit}$, i.e. the wage bill of the firm for each labor type.

That contract and regular labor markets are segmented (we observe no increase in the number of regular workers) suggests that the tasks that contract workers and regular workers engage in are complementary in production. In light of this, it is possible to provide an exogenous estimate of the elasticity of substitution, σ, between new entrants into casual positions and incumbent regular workers. If $\sigma < 1$, the new entrant casual workers and incumbent regular workers engage in tasks that are complementary. If $\sigma > 1$, then these workers engage in tasks that are substitutable.

$$\sigma \propto \frac{\partial \log w_m^p}{\partial Temperature} / \frac{\partial \log L_m^c}{\partial Temperature} = \frac{\partial \log w_m^p}{\partial \log L_m^c} = 0.436 \tag{17}$$

These results suggest that a 1% increase in the number of contract workers is associated with a 0.436% increase in the average wage of regular manufacturing workers. To the degree that new entrants out of agriculture and incumbent casual workers are substitutable in tasks, this would indicate that, on average, contract and regular workers in regulated firms engage in complementary production tasks.

With these parameters in hand, I construct L_{it}^{CES} for each firm and then estimate productivity using the CES labor input in place of the Cobb-Douglas Labor input.

Results Table D16 presents the productivity results for the differences-in-temperature exercise. I fail to reject the null hypothesis that there is no relative increase in output per worker, however, I do estimate relative increases in TFPR, measured using the standard Cobb-Douglas approach and the nested Cobb-Douglas approach. For both measures of

TFPR I do not estimate any differential effect of temperature between labor regulation environments for unregulated firms. For output per worker I estimate a differential effect of temperature across labor regulation environments that is significant at the 10% level.

Table D16: The Effects of Temperature on Productivity

	(1) log Output per Worker	(2) log TFPR	(3) log TFPR (CES)
Regression Estimates:			
Daily Average Temperature (°C): γ_1	-0.0759	-0.0734***	-0.0736***
	(0.0469)	(0.0227)	(0.0239)
Temperature $\times$ Flexible: γ_2	0.0546	0.0536**	0.0545*
	(0.0551)	(0.0253)	(0.0262)
Temperature $\times$ Below Threshold: γ_3	0.0278	0.0638*	0.0646
	(0.0485)	(0.0354)	(0.0377)
Temperature $\times$ Flexible $\times$ Below Threshold: γ_4	0.0360	-0.0553	-0.0582
	(0.0612)	(0.0397)	(0.0425)
Formal Tests			
Difference Above Threshold: $H_0 : \gamma_2 = 0$	0.0546	0.0536**	0.0545*
	(0.0535)	(0.0253)	(0.0262)
Difference Below Threshold: $H_0 : \gamma_2 + \gamma_4 = 0$	0.090	-0.002	-0.003
	(0.058)	(0.029)	(0.030)
Sector $\times$ District Fixed Effects	Yes	Yes	Yes
Sector $\times$ Year Fixed Effects	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes
State-Year Time Trends	Yes	Yes	Yes
Observations	88,846	88,846	88,846

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Regressions are weighted using sampling weights provided by the Central Statistics Office. "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. District $\times$ Sector and Sector $\times$ 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).

D.7 Discontinuity-in-Temperature Approach

In this section I introduce a secondary identification strategy, which explores whether there is a discontinuous change in the effects of temperature at the regulatory threshold within each labor regulation environment.

D.7.1 Research Design

The purpose of this second research design is to alleviate concerns about systematic differences between labor regulation environments by identifying the differential effects of temperature within the same labor regulation environment as well as provide a more credible test for the hypothesis that unregulated firms are more responsive than regulated firms. Firms on either side of the regulatory threshold are affected by the same temperature exposure and so should not be differentially affected other than as a result of any differential response to the labor regulation environment. By looking at firms that are close to the regulatory threshold they should be similar in other respects as well, except that unregulated firms face fewer constraints in hiring workers. We should expect a discontinuous positive effect of temperature on firm outcomes moving from regulated to unregulated in rigid labor markets, and a smaller discontinuous effect in flexible labor markets because moving above the regulatory threshold is less costly.

Equation 18 presents the empirical specification for this research design,

$$\begin{aligned}
\log Y_{ijrdst} \quad = \quad & \gamma_1 f(w_{dt}) + \gamma_2 f(w_{dt}) \times \textsc{Flexible}_s \\
& + \gamma_3 f(w_{dt}) \times \textsc{Below}_r + \ \gamma_4 f(w_{dt}) \times \textsc{Below}_r \times \textsc{Flexible}_s \\
& + \ \delta_1 \textsc{Below}_r + \delta_2 \textsc{Below}_r \times \textsc{Flexible}_s + \delta_3 f(\textsc{Firm Size}_{ijdt}) \\
& + \ \delta_4 f(\textsc{Firm Size}_{ijdt}) \times f(w_{dt}) + \delta_5 f(\textsc{Firm Size}_{ijdt}) \times \textsc{Flexible}_s \\
& + \ \delta_6 f(\textsc{Firm Size}_{ijdt}) \times f(w_{dt}) \times \textsc{Flexible}_s \\
& + \ \alpha_{jd} + \alpha_{jt} + \phi_s t + \varepsilon_{ijdt}.
\end{aligned} \tag{18}$$

Equation 18 is similar in essence to equation 1, except that the fixed effects are no longer regulatory group specific as we wish to make comparisons between regulated and unregulated firms at the regulatory threshold. I include a variable which defines whether a firm is below the regulatory threshold, $\textsc{Below}_r$, and include the interaction of this variable with the labor regulation environment, $\textsc{Below}_r \times \textsc{Flexible}_s$. In addition, I include variables controlling for firm size relative to the threshold (the running variable), on each side of the threshold, as well as a full set of interaction variables between relative firm size, weather and the labor regulation environment. In the main specification I use a linear polynomial for firm-size, weight observations using a triangular kernel, and restrict the window to be firms within 50 employees of the regulatory threshold. Results are robust to including quadratic polynomials, uniform weights, and narrowing the bandwidth further.

The key identification assumption for this approach 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 approach it does not necessarily matter if the continuity assumption is violated as long as the other factors that vary at the regulatory threshold do not differentially effect the response of firms to changes in temperature. This is, arguably, a much weaker identification assumption. In the context of exploring the effects of labor regulations that vary with firm-size, one may be concerned that there is bunching in the firm-size distribution, but, again, bunching is only a concern in this context if it varies in response to temperature changes. In Appendix D.7.3 I show that there is limited evidence of bunching in the firm-size distribution and that, more importantly, bunching estimates do not vary with temperature.

D.7.2 Results

Table D17 presents the results of the discontinuity-in-temperature analysis. The purpose of this second research design is to alleviate concerns about systematic differences between labor regulation environments by identifying the differential effects of temperature within the same labor regulation environment. The coefficient of interest is, γ_3, capturing the discontinuous effect of temperature on firms just below the regulatory threshold in rigid labor markets. Consistent with the results from the differences-in-temperature analysis we observe discontinuous increases in output and employment, with larger effects on contract workers. In Table D18 we also observe discontinuous increases in productivity. Despite the discontinuous expansion in activity for unregulated firms the overall effect of temperature is negative for all outcomes – the discontinuous expansions are relative. Finally, I do not observe any discontinuous effects of temperature at the regulatory threshold in more flexible labor regulation environments. These results are robust to using a quadratic polynomial for the running variable (Table D20), to using uniform, as opposed to triangular, weights (Table D21), and to using different bandwidths (Tables D22, D23, and D24).

Table D17: The Differential Effects of Temperature on Manufacturing Firms at the Regulatory Threshold

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Regression Estimates					
Daily Average Temperature (°C): γ_1	-0.150***	-0.296***	0.00147	-0.00217	-0.0444***
	(0.0446)	(0.0917)	(0.0102)	(0.0282)	(0.0143)
Temperature × Flexible: γ_2	0.151**	0.275**	-0.0139	0.0108	0.0686**
	(0.0545)	(0.108)	(0.0185)	(0.0398)	(0.0277)
Temperature × Below Threshold: γ_3	0.0307***	0.135***	0.00969	0.00216	0.00799
	(0.0102)	(0.0385)	(0.0128)	(0.0102)	(0.00916)
Temperature × Flexible × Below Threshold: γ_4	-0.0248*	-0.124***	-0.00994	-0.000425	0.00323
	(0.0134)	(0.0412)	(0.0135)	(0.0120)	(0.0106)
Fixed Effects	Sector × District & Sector × Year				
Other Controls	Monsoon Rainfall (inc. interactions), Linear State × Year Time Trends & Running variables (inc. interactions)				
Bandwidth	50	50	50	50	50
Polynomial	Linear	Linear	Linear	Linear	Linear
Kernel	Triangle	Triangle	Triangle	Triangle	Triangle
Observations	22,999	7,985	22,999	7,985	22,999
Formal Tests					
Discontinuity (Pro-Worker): $H_0 : \gamma_3 = 0$	0.0307***	0.135***	0.00969	0.00216	0.00799
	(0.0102)	(0.0385)	(0.0128)	(0.0102)	(0.00916)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	0.005	0.011	-0.000	0.002	0.011**
	(0.008)	(0.011)	(0.005)	(0.004)	(0.005)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. "Discontinuity in Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated. "Discontinuity in Non Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated in non-rigid states. 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).

Table D18: The Differential Effects of Temperature on Firm Productivity at the Regulatory Threshold

	(1) log Output per Worker	(2) log TFPR	(3) log TFPR (CES)
Regression Estimates			
Daily Average Temperature (°C): γ_1	-0.107	-0.0722***	-0.0714***
	(0.0733)	(0.0166)	(0.0162)
Temperature $\times$ Flexible: γ_2	0.141*	0.0533	0.0507
	(0.0712)	(0.0325)	(0.0328)
Temperature $\times$ Below Threshold: γ_3	0.0195**	0.0101	0.00921
	(0.00751)	(0.00725)	(0.00665)
Temperature $\times$ Flexible $\times$ Below Threshold: γ_4	-0.0221**	-0.0127	-0.0123
	(0.0102)	(0.0109)	(0.0106)
Sector $\times$ District Fixed Effects	Yes	Yes	Yes
Sector $\times$ Year Fixed Effects	Yes	Yes	Yes
Rainfall Controls	Yes	Yes	Yes
State $\times$ Year Time Trends	Yes	Yes	Yes
Bandwidth	50	50	50
Kernel	Triangle	Triangle	Triangle
Observations	22,999	22,999	22,999
Formal Tests			
Discontinuity (Pro-Worker): $H_0 : \gamma_3 = 0$	0.0195**	0.0101	0.00921
	(0.00751)	(0.00725)	(0.00665)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	-0.002	-0.002	-0.003
	(0.008)	(0.007)	(0.007)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. "Discontinuity in Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated. "Discontinuity in Non Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated in non-rigid states. 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).

D.7.3 Bunching in the Firm-Size Distribution

The key identification assumption for a regression discontinuity design is continuity – . In the context of labor regulations the first-order concern, relating to a violation of continuity, is that firms select around the regulatory threshold resulting in bunching around the regulatory threshold. For identification in the context of the discontinuity-in-temperature research design, bunching is not necessarily a problem. The parameter of interest is the effect of temperature on firms at the threshold. Bunching is only an identification concern if it is driven by short-run changes in temperature.

First, I explore the degree to which bunching is observed in the data. In Figure D6 I plot the firm-size distribution for four different groups for the year 2003.[29] In panel a) we see the firm-size distribution for all firms. There is no visible evidence of a discontinuous break in the firm-size distribution to indicate that firms are sorting around any regulatory thresholds. In panel b) I restrict attention to West Bengal, a pro-worker state with a regulatory threshold of 50 workers. In panel c) we look at the other pro-worker states, Odisha and Maharashtra, that have a regulatory threshold at 100 workers. In panel d) we look at the remaining non pro-worker states. In all cases I do not observe any visible evidence of sorting around the regulatory threshold. In Figure D7 I use formally test the presence of bunching using McCrary tests. Again we find little evidence of bunching to the left of the regulatory threshold. In Panel a) we observe limited bunching on the wrong side of the 100-worker regulatory threshold for firms in Odisha and Maharashtra. In West Bengal there is an indication that some bunching could occur just before the 50-worker regulatory threshold, however, focusing on an individual state reduces the number of observations around the threshold, meaning that small changes in density are exacerbated, potentially leading to spurious inferences.

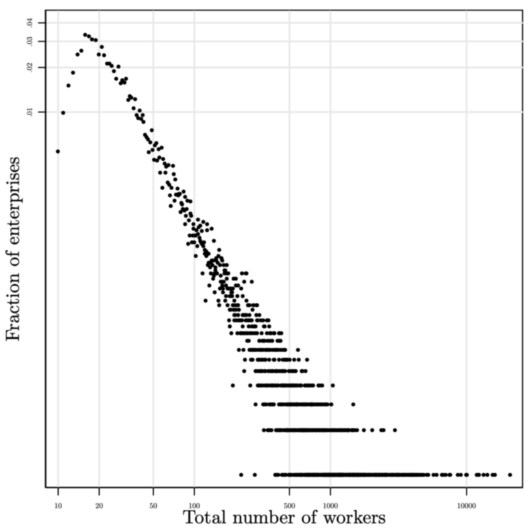
While there is limited direct evidence of bunching in the data, several caveats need to be noted. First, the ASI reports the average number of workers in a given year. Second, the sampling structure of the ASI means that firms are randomly sampled below the 100-worker regulatory threshold, potentially resulting in spurious changes in the density of observations, even after accounting for sampling weights, which are likely imperfect. Bunching around the regulatory threshold may occur even if I do not observe it directly in the data due to measurement error and sampling issues. Nevertheless, bunching per se is not an identification issue. What matters is that bunching doesn't respond to year-to-year changes in temperature, a much weaker identification assumption. To explore this directly, I estimate state-year specific bunching estimates and regress these estimates on temperature, rainfall, and the interaction of these variables with the policy variable to explore differential bunching

[29] 2003 has the most observations and is chosen to maximize power. The inferences made here are robust to using alternative years.

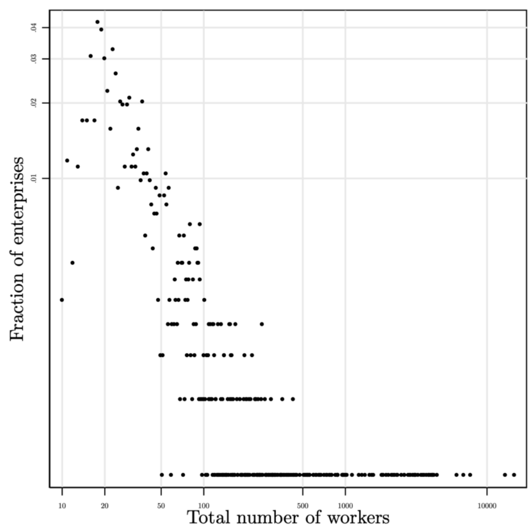
with respect to the rigidity of the labor market.[30] The results of this exercise are reported in Table D19. In all cases I fail to reject the null hypothesis that there is no relationship between temperature and bunching around the regulatory threshold.

[30]In a number of cases bunching estimates are based on a small number of observations and lead to some vary large, and likely spurious, discontinuities. To account for this I trim the absolute value of the bunching estimates at the 95th percentile.

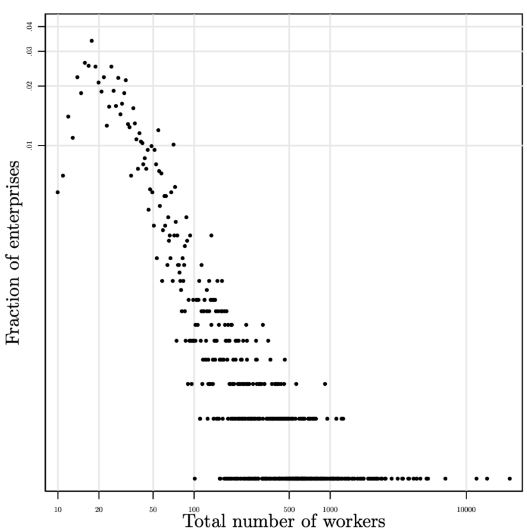
Figure D6: The Firm-Size Distribution



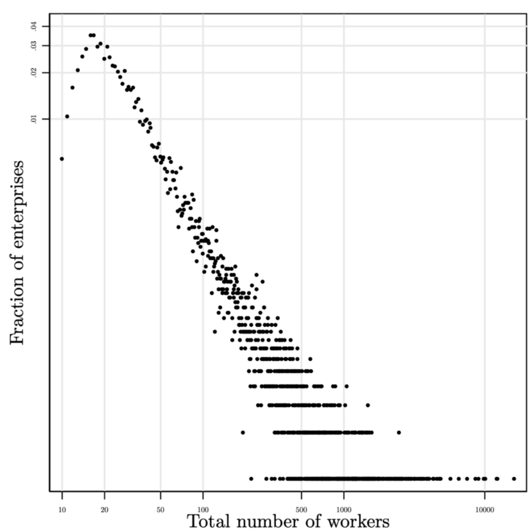
(a) All States



(b) West Bengal (Pro-Worker)

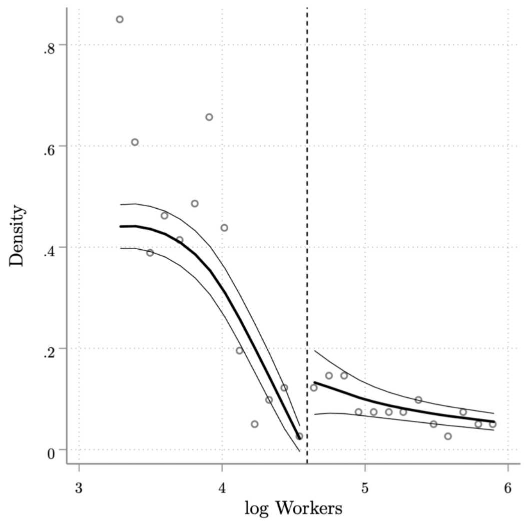


(c) Other Pro-Worker States

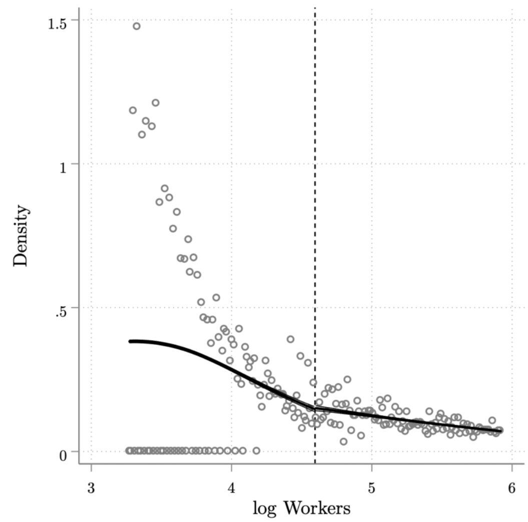


(d) Non Pro-Worker States

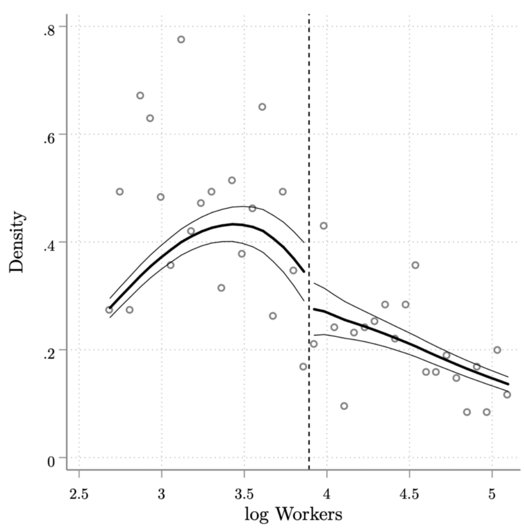
Figure D7: Formal Bunching Tests



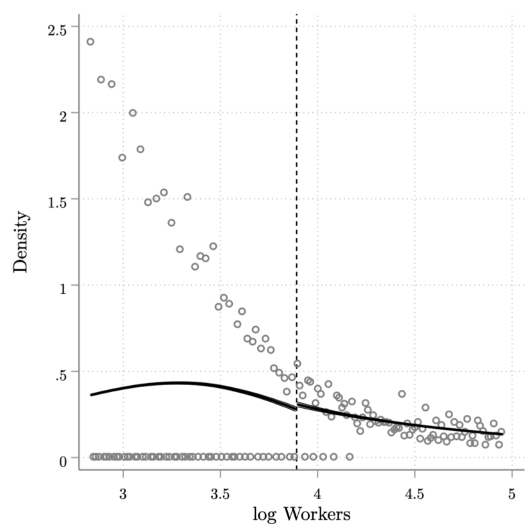
(a) Pro-Worker (Threshold = 100)



(b) Not Pro-Worker (Threshold = 100)



(c) West Bengal (Threshold = 50)



(d) Not West Bengal (Threshold = 50)

Table D19: Do Bunching Estimates Vary with Temperature?

	(1) Bunching Estimates	(2) Bunching Estimates	(3) Bunching Estimates	(4) Bunching Estimates
Daily Average Temperature (°C)	-0.0145	-0.00555	-0.0668	-0.148
	(0.0152)	(0.0170)	(0.237)	(0.235)
Temperature × Flexible		-0.0110		0.0877
		(0.00875)		(0.368)
State Fixed Effects	No	No	Yes	Yes
Year Fixed Effects	No	No	Yes	Yes
Rainfall Controls	Yes	Yes	Yes	Yes
Observations	117	117	117	117

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. The data is trimmed to exclude the absolute value of bunching estimates that exceed the 95th percentile.

D.7.4 Quadratic Polynomials

Table D20: The Differential Effects of Temperature on Manufacturing Firms at the Regulatory Threshold (Quadratic Polynomials)

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Regression Estimates					
Daily Average Temperature (°C): γ_1	-0.160***	-0.286***	0.0000343	-0.0112	-0.0505***
	(0.0487)	(0.0853)	(0.00934)	(0.0320)	(0.0132)
Temperature × Flexible: γ_2	0.150**	0.236**	-0.0138	0.00593	0.0700**
	(0.0546)	(0.106)	(0.0189)	(0.0431)	(0.0273)
Temperature × Below Threshold: γ_3	0.0403**	0.129*	0.00419	0.00597	0.00969
	(0.0155)	(0.0644)	(0.0165)	(0.0151)	(0.00668)
Temperature × Flexible × Below Threshold: γ_4	-0.0118	-0.115*	-0.00854	0.000980	0.00527
	(0.0131)	(0.0614)	(0.0160)	(0.0162)	(0.00830)
Fixed Effects	Sector × District & Sector × Year				
Other Controls	Monsoon Rainfall (inc. interactions), Linear State × Year Time Trends & Running variables (inc. interactions)				
Bandwidth	50	50	50	50	50
Polynomial	Quadratic	Quadratic	Quadratic	Quadratic	Quadratic
Kernel	Triangle	Triangle	Triangle	Triangle	Triangle
Observations	22,999	7,985	22,999	7,985	22,999
Formal Tests					
Discontinuity (Pro-Worker): $H_0 : \gamma_3 = 0$	0.0403**	0.129*	0.00419	0.00597	0.00969
	(0.0155)	(0.0644)	(0.0165)	(0.0151)	(0.00668)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	0.028***	0.014	-0.004	0.007	0.015**
	(0.008)	(0.016)	(0.005)	(0.006)	(0.006)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. "Discontinuity in Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated. "Discontinuity in Non Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated in non-rigid states. 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).

D.7.5 Uniform Weights

Table D21: The Differential Effects of Temperature on Manufacturing Firms at the Regulatory Threshold (Uniform Weights)

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Regression Estimates					
Daily Average Temperature (°C): γ_1	-0.115**	-0.218**	-0.0204**	-0.00371	-0.0330
	(0.0511)	(0.101)	(0.00878)	(0.0198)	(0.0193)
Temperature $\times$ Flexible: γ_2	0.0968	0.160	0.0137	-0.0116	0.0360
	(0.0611)	(0.124)	(0.0173)	(0.0402)	(0.0273)
Temperature $\times$ Below Threshold: γ_3	0.00869	0.132**	0.00683	-0.0135*	-0.00610
	(0.0178)	(0.0581)	(0.00457)	(0.00655)	(0.00603)
Temperature $\times$ Flexible $\times$ Below Threshold: γ_4	-0.00494	-0.124*	-0.0104	0.0192*	0.0166*
	(0.0187)	(0.0598)	(0.00603)	(0.00978)	(0.00815)
Fixed Effects	Sector $\times$ District & Sector $\times$ Year				
Other Controls	Monsoon Rainfall (inc. interactions), Linear State $\times$ Year Time Trends & Running variables (inc. interactions)				
Bandwidth	50	50	50	50	50
Polynomial	Linear	Linear	Linear	Linear	Linear
Kernel	Uniform	Uniform	Uniform	Uniform	Uniform
Observations	23,520	8,172	23,520	8,172	23,520
Formal Tests					
Discontinuity (Pro-Worker): $H_0 : \gamma_3 = 0$	0.00869	0.132**	0.00683	-0.0135*	-0.00610
	(0.0178)	(0.0581)	(0.00457)	(0.00655)	(0.00603)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	0.004	0.008	-0.004	0.006	0.011*
	(0.006)	(0.011)	(0.004)	(0.007)	(0.005)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. "Discontinuity in Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated. "Discontinuity in Non Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated in non-rigid states. 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).

D.7.6 Different Bandwidths

Table D22: The Differential Effects of Temperature on Manufacturing Firms at the Regulatory Threshold (Bandwidth of 40 Workers)

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Regression Estimates					
Daily Average Temperature (°C): γ_1	-0.121**	-0.333***	0.00535	0.000106	-0.0385***
	(0.0498)	(0.0891)	(0.0152)	(0.0338)	(0.0116)
Temperature × Flexible: γ_2	0.126**	0.325**	-0.0163	0.00810	0.0671**
	(0.0544)	(0.120)	(0.0212)	(0.0441)	(0.0282)
Temperature × Below Threshold: γ_3	0.0291***	0.139***	0.00883	0.00745	0.0123
	(0.00933)	(0.0451)	(0.0170)	(0.0125)	(0.00968)
Temperature × Flexible × Below Threshold: γ_4	-0.0189	-0.130**	-0.00972	-0.00339	-0.000116
	(0.0133)	(0.0485)	(0.0175)	(0.0147)	(0.0115)
Fixed Effects	Sector × District & Sector × Year				
Other Controls	Monsoon Rainfall (inc. interactions), Linear State × Year Time Trends & Running variables (inc. interactions)				
Bandwidth	40	40	40	40	40
Polynomial	Linear	Linear	Linear	Linear	Linear
Kernel	Triangle	Triangle	Triangle	Triangle	Triangle
Observations	17,893	6,213	17,893	6,213	17,893
Formal Tests					
Discontinuity (Pro-Worker): $H_0 : \gamma_3 = 0$	0.0291***	0.139***	0.00883	0.00745	0.0123
	(0.00933)	(0.0451)	(0.0170)	(0.0125)	(0.00968)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	0.010	0.008	-0.000	0.004	0.021**
	(0.009)	(0.012)	(0.004)	(0.005)	(0.005)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. "Discontinuity in Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated. "Discontinuity in Non Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated in non-rigid states. 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).

Table D23: The Differential Effects of Temperature on Manufacturing Firms at the Regulatory Threshold (Bandwidth of 30 Workers)

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Regression Estimates					
Daily Average Temperature (°C): γ_1	-0.0816 (0.0670)	-0.356*** (0.0660)	0.0164 (0.0244)	0.0114 (0.0368)	-0.0466*** (0.0159)
Temperature × Flexible: γ_2	0.0925 (0.0677)	0.381*** (0.119)	-0.0316 (0.0269)	-0.00607 (0.0476)	0.0759** (0.0346)
Temperature × Below Threshold: γ_3	0.0149 (0.0111)	0.108* (0.0584)	0.0110 (0.0185)	0.0156 (0.0224)	0.0145* (0.00732)
Temperature × Flexible × Below Threshold: γ_4	0.0164 (0.0157)	-0.0945 (0.0624)	-0.0156 (0.0190)	-0.0123 (0.0248)	0.000170 (0.00906)
Fixed Effects	Sector × District & Sector × Year				
Other Controls	Monsoon Rainfall (inc. interactions), Linear State × Year Time Trends & Running variables (inc. interactions)				
Bandwidth	30	30	30	30	30
Polynomial	Linear	Linear	Linear	Linear	Linear
Kernel	Triangle	Triangle	Triangle	Triangle	Triangle
Observations	12,935	4,524	12,935	4,524	12,935
Formal Tests					
Discontinuity (Pro-Worker): $H_0 : \gamma_3 = 0$	0.0149 (0.0111)	0.108* (0.0584)	0.0110 (0.0185)	0.0156 (0.0224)	0.0145* (0.00732)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	0.031*** (0.010)	0.014 (0.017)	-0.004 (0.005)	0.003 (0.006)	0.015** (0.005)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. "Discontinuity in Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated. "Discontinuity in Non Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated in non-rigid states. 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).

Table D24: The Differential Effects of Temperature on Manufacturing Firms at the Regulatory Threshold (Bandwidth of 20 Workers)

	(1) log Total Output	(2) log Workers (Contract)	(3) log Workers (Regular)	(4) log Day Wage (Contract)	(5) log Day Wage (Regular)
Regression Estimates					
Daily Average Temperature (°C): γ_1	-0.0270	-0.265***	0.00826	0.0247	-0.0208
	(0.0980)	(0.0841)	(0.0485)	(0.0518)	(0.0252)
Temperature $\times$ Flexible: γ_2	0.0629	0.306	-0.0483	0.0154	0.0504
	(0.0948)	(0.177)	(0.0417)	(0.0612)	(0.0453)
Temperature $\times$ Below Threshold: γ_3	-0.00290	0.0502	0.0111	0.0532	0.0115**
	(0.00550)	(0.0589)	(0.0243)	(0.0336)	(0.00421)
Temperature $\times$ Flexible $\times$ Below Threshold: γ_4	0.0597**	-0.0249	-0.0151	-0.0537	0.00464
	(0.0221)	(0.0678)	(0.0256)	(0.0375)	(0.00648)
Fixed Effects	Sector $\times$ District & Sector $\times$ Year				
Other Controls	Monsoon Rainfall (inc. interactions), Linear State $\times$ Year Time Trends & Running variables (inc. interactions)				
Bandwidth	20	20	20	20	20
Polynomial	Linear	Linear	Linear	Linear	Linear
Kernel	Triangle	Triangle	Triangle	Triangle	Triangle
Observations	8,198	2,943	8,198	2,943	8,198
Formal Tests					
Discontinuity (Pro-Worker): $H_0 : \gamma_3 = 0$	-0.00290	0.0502	0.0111	0.0532	0.0115**
	(0.00550)	(0.0589)	(0.0243)	(0.0336)	(0.00421)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	0.056**	0.025	-0.003	-0.000	0.016**
	(0.020)	(0.032)	(0.008)	(0.001)	(0.005)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. "Discontinuity in Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated. "Discontinuity in Non Pro-Worker States" presents the differential effect of temperature on firms at the regulatory threshold going from regulated to unregulated in non-rigid states. 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).