Temperature, Labor Reallocation, and Industrial Production: Evidence from India
Online Appendix

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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).

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Figure A1: Agricultural Production, Cultivated Area, Yields and Prices by Crop
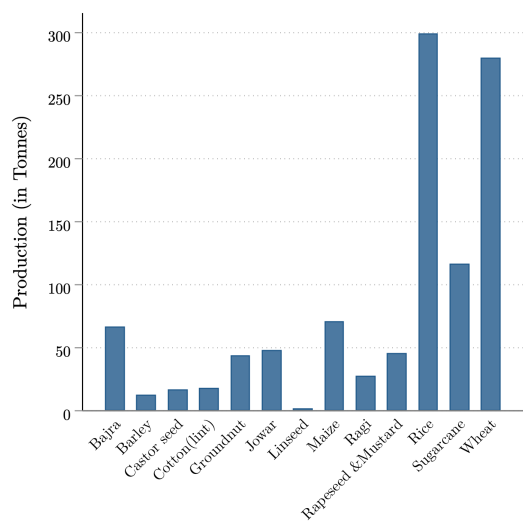
(a) Production ('000 tonnes)
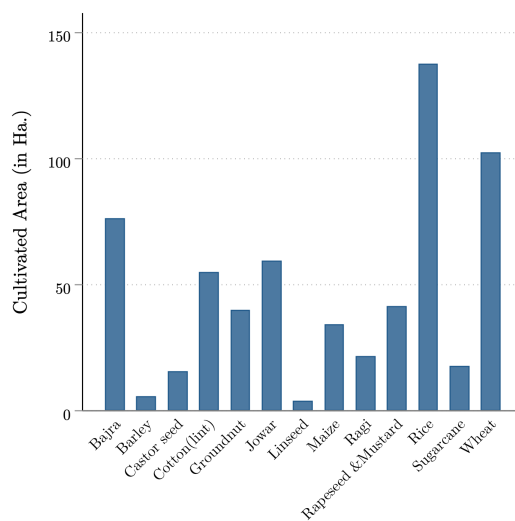
(b) Cultivated Area ('000 Ha.)

(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 agricu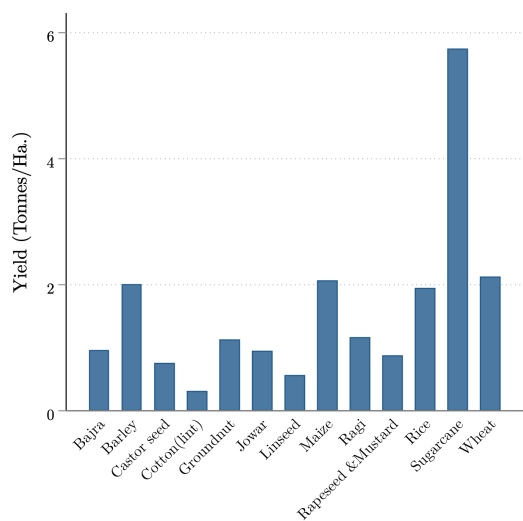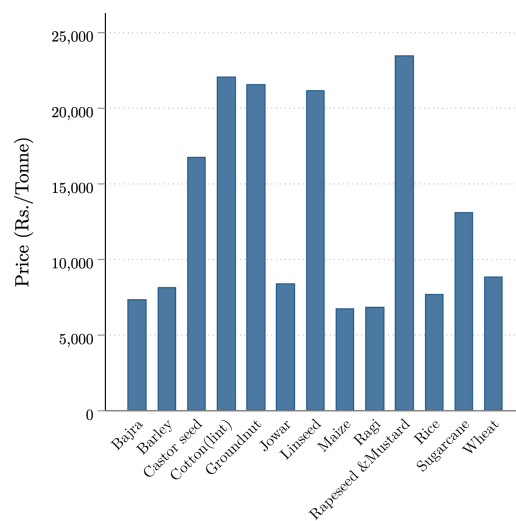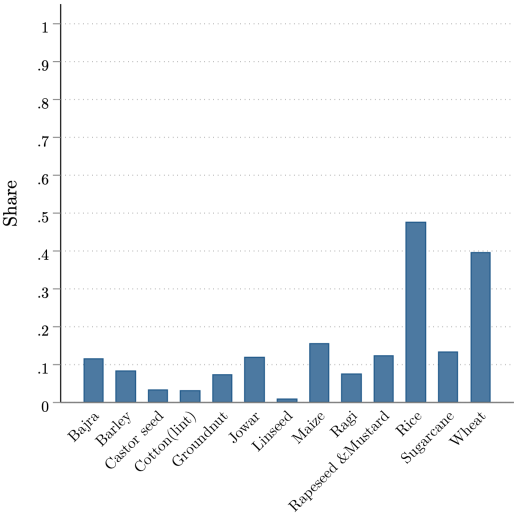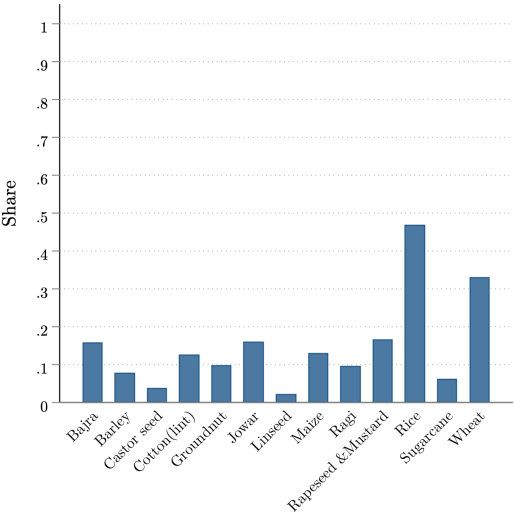ltural yields and weather is highly nonlinear (Schlenker and Roberts, 2009; Auffhammer and Schlenker, 2014). To account for the relevance of any non-linearities, I engage in two exercises. First, I apply the concept of growing degree days, which measure the amount of time a crop is exposed between a 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,

$$
GDD_{d;t_l;t_h} = \begin{cases} 0 \text{ if } t_d \leq t_l \\ t_d - t_l \text{ if } t_l < t_d < t_h \\ t_h - t_l \text{ if } t_h \leq t_d \end{cases} \tag{1}
$$

These daily measures are then summed over the period of interest.[1] 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,

$$
f(w_{dt}) = \beta_1 GDD_{dt;t_l;t_h} + \beta_2 GDD_{dt;t_h;\infty} + \beta_3 Rain_{dt} \tag{2}
$$

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

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[1]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,

$$f(w_{dt}) = \sum_{j=1}^{10} \beta_j Temp_{dtj} + \beta_3 Rain_{dt} \tag{3}$$

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) $t_L = 23, t_H = \infty$	-0.00800*** (0.00207)	-0.00777*** (0.00182)	0.000227 (0.000614)
DEGREE DAYS (10 days) $t_L = 0, t_H = 23$	-0.000871 (0.00153)	-0.00354* (0.00213)	-0.00267 (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
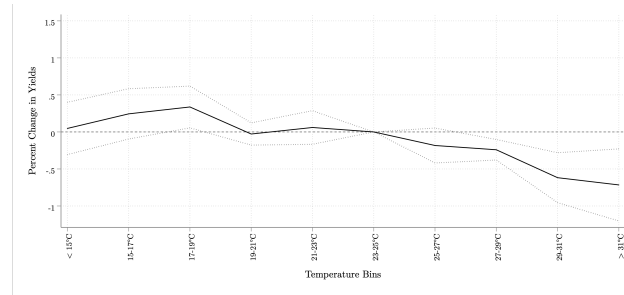
(a) Yield
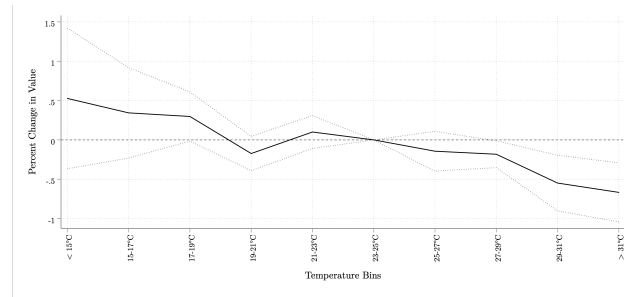
(b) Value
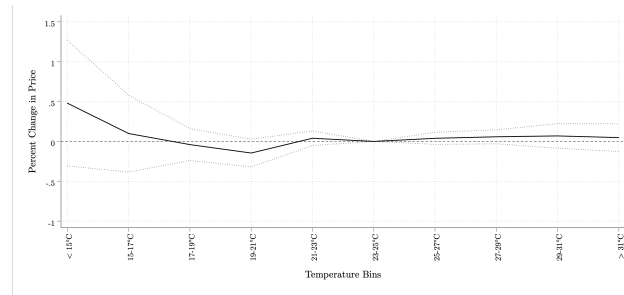
(c) Price

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

	logAGRICULTURAL OUTCOMES		
	YIELD (ALL CROPS)	VALUE (ALL CROPS)	PRICE (ALL CROPS)
DAILY AVERAGE TEMPERATURE (°C)	-0.122*** (0.0296)	-0.123*** (0.0270)	-0.00158 (0.00949)
1-YEAR LAG	No	No	No
1-YEAR LEAD	No	No	No
DAILY AVERAGE TEMPERATURE (°C)	-0.104*** (0.0238)	-0.113*** (0.0231)	-0.00831 (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. The first row of results are the main results from Table 1, without controls for lags and leads. 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 ?, 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 (**???**).

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*** (0.0333)	-0.120*** (0.0318)	0.00683 (0.00955)
MONSOON RAINFALL (100mm)	0.0212*** (0.00347)	0.0168*** (0.00366)	-0.00442** (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*** (0.0333)	-0.158*** (0.0337)	
MONSOON RAINFALL (100mm)	0.0212*** (0.00347)		0.0274*** (0.00389)
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 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*** (0.0263)	-0.116*** (0.0245)	-0.000529 (0.00913)
Monsoon Rainfall (Shock)	0.0514*** (0.0104)	0.0487*** (0.0105)	-0.00279 (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*** (0.0263)	-0.139*** (0.0291)	
Monsoon Rainfall (Shock)	0.0514*** (0.0104)		0.0719*** (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*** (0.0285)	-0.119*** (0.0261)	-0.000886 (0.00952)
MONSOON RAINFALL (100mm)	0.0112*** (0.00356)	0.00963*** (0.00342)	-0.00152 (0.00169)
TEMPERATURE × RAINFALL	0.00152 (0.000982)	0.00188** (0.000945)	0.000362 (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
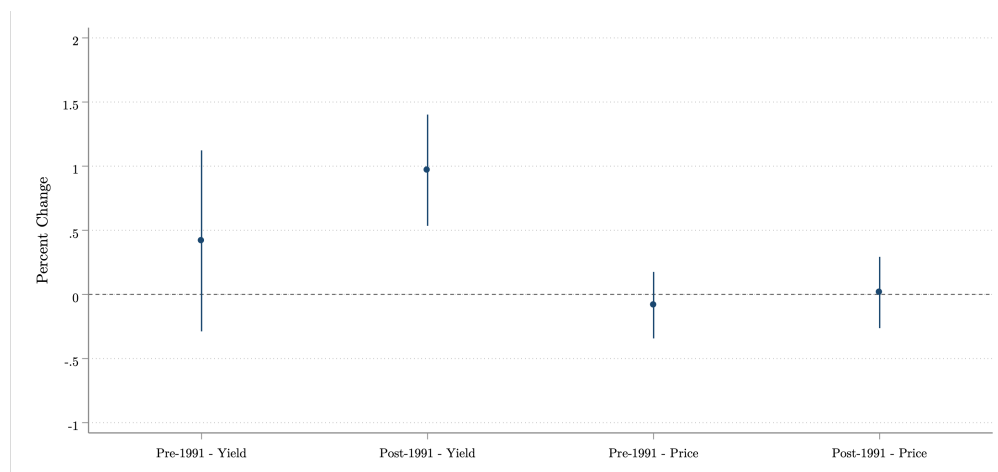
(a) Temperature Controls
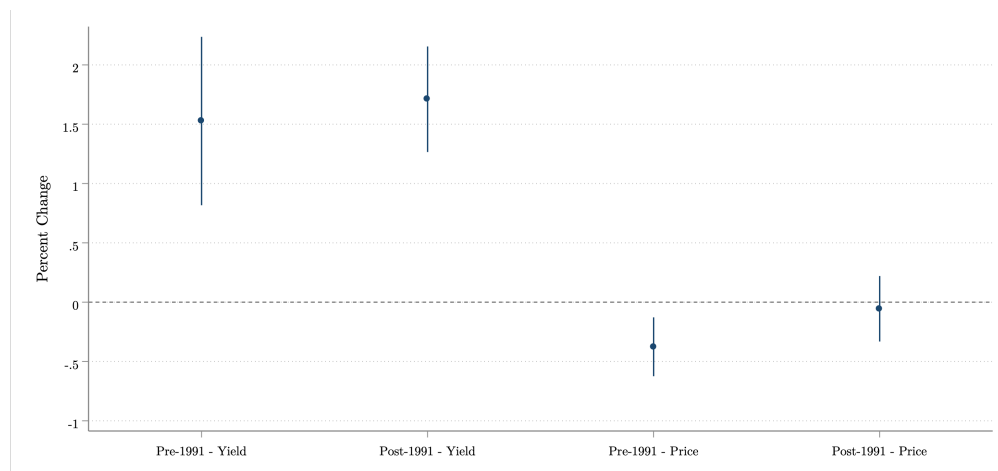
(b) No Temperature Controls

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
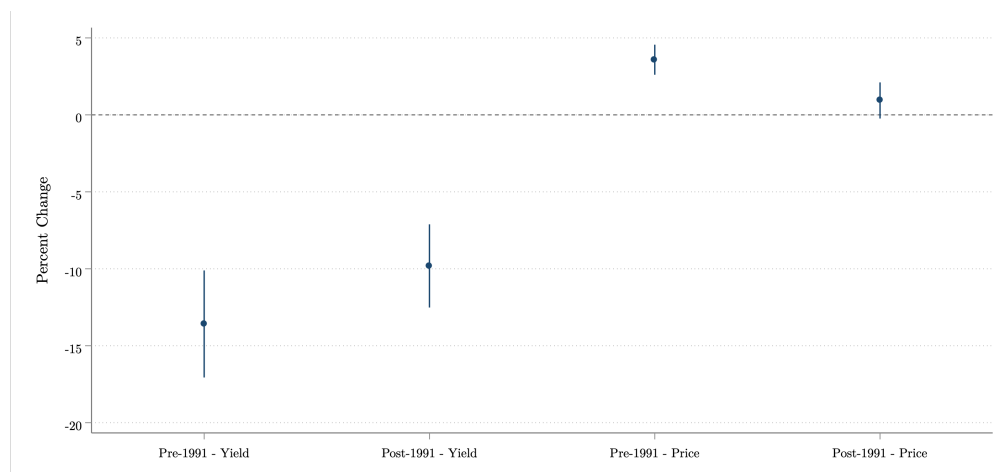
(a) Rainfall Controls
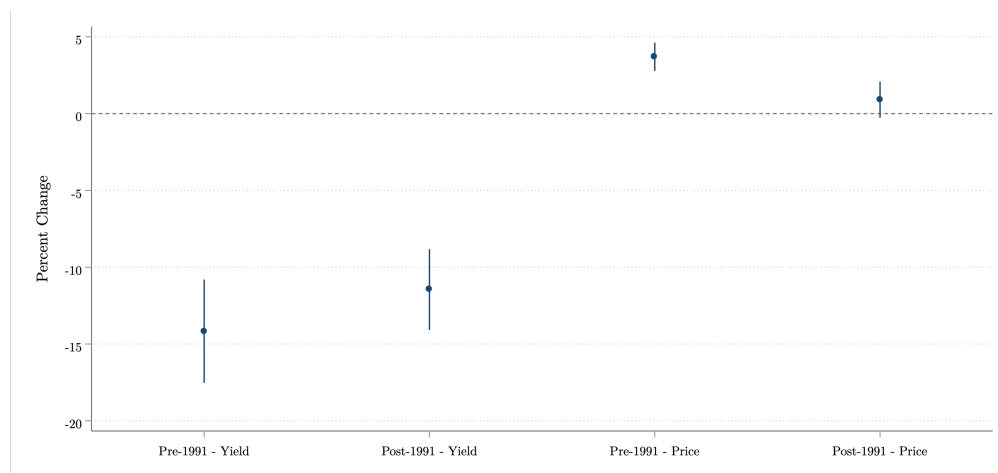
(b) No Rainfall Controls

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*** (0.0342)	-0.151*** (0.0339)	
DAT × IRRIGATION SHARE	0.0212 (0.0152)	0.0258 (0.0159)	
MONSOON RAINFALL (100mm)	0.0179*** (0.00422)		0.0242*** (0.00506)
RAIN × IRRIGATION SHARE	-0.0168** (0.00764)		-0.0146* (0.00762)
IRRIGATION SHARE	-0.112 (0.372)	-0.319 (0.393)	0.431*** (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).
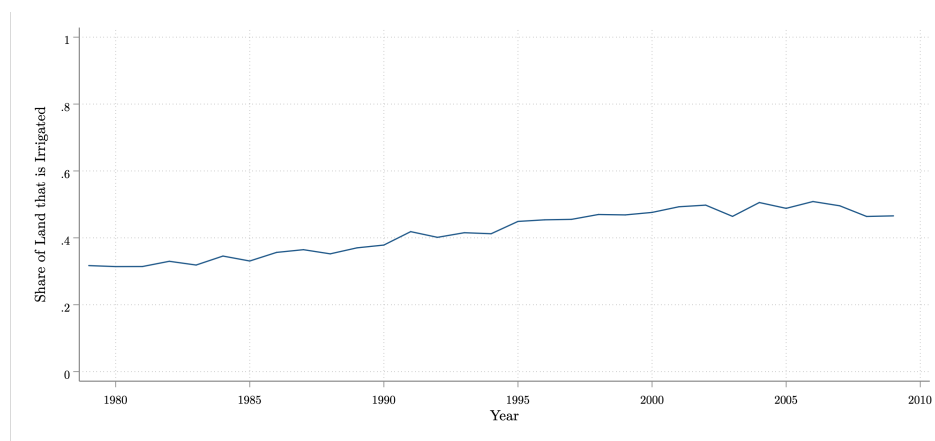
Notes: The share of irrigated land is defined as the total area in '000 hectares that is irrigated by canals, tanks, tubewells, other wells, or other sources, divided by the total area planted in '000 hectares.

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*** (0.0111)	-0.158*** (0.0207)	-0.100*** (0.0144)
DAT × IRRIGATION SHARE	-0.000934 (0.00456)	0.0317* (0.0181)	-0.000183 (0.00449)
MONSOON RAINFALL (100mm)	0.0185*** (0.00250)	0.0171*** (0.00404)	0.0201*** (0.00292)
RAIN × IRRIGATION SHARE	-0.0265*** (0.00429)	-0.0448*** (0.00812)	-0.0248*** (0.00494)
IRRIGATION SHARE	0.323*** (0.118)	-0.369 (0.433)	0.369*** (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).[2] Given prices in sector j, p_{ij}, and total income, w_iL_i, each worker maximizes

$$U_i = (C_{ia} - \bar{a})^\alpha C_{im}{}^{1-\alpha} \tag{4}$$

which they maximize subject to their budget constraint,

$$p_{ia}C_{ia} + p_{im}C_{im} \leq L_iw_i \tag{5}$$

Worker demand for goods in agriculture, $D_{ia} = p_{ia}\bar{a} + \alpha(L_iw_i - p_{ia}\bar{a})$. For manufactured goods $D_{im} = (1 - \alpha)(L_iw_i - p_{ia}\bar{a})$. 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_iw_i).

Production

There are 2 goods that can be produced in each location i: agricultural good a and manufactured goods m.[3] I assume that all regions have access to the same technology and so

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[2]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).

[3]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,

$$Y_j = A_j F_j(L_j) \tag{6}$$

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,

$$p_a A_a F_a'(L_a) = w = p_m A_m F_m'(L_m) \tag{7}$$

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,

$$
\begin{aligned}
C_a &= A_a F_a(L_a) \\
C_m &= A_m F_m(L_m)
\end{aligned}
\tag{8}
$$

Maximization of equation 4 implies that each worker consumes agricultural goods such that,

$$p_a C_a = \bar{a} + \frac{\alpha p_m C_m}{1 - \alpha} \tag{9}$$

Combining this result with the profit maximization condition (equation 7), the labor market clearing condition ($L_m = 1 - L_a$), and the fact that total production must equal total consumption yields,

$$\Omega(L_m) = \frac{\bar{a}}{A_a} \tag{10}$$

where,

$$\Omega(L_m) \equiv F_m(L_m) - \frac{F_m{}'(L_m)F_a(1-L_a)}{F_a{}'(1-L_a)} \tag{11}$$

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,

$$L_m = \Omega^{-1}\left(\frac{\bar{a}}{A_a}\right) \tag{12}$$

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,

$$p_a A_{i'a} F_{i'a}{}'(L_{i'a}) = p_m A_{i'm} F_{i'm}{}'(L_{i'm}) \tag{13}$$

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 7 and 13. Taking the ratio of these equations provides the following equality,

$$\frac{F_{im}{}'(L_{im})}{F_{ia}{}'(L_{ia})} = \frac{A_{ia} A_{i'm}}{A_{i'a} A_{im}} \frac{F_{i'm}{}'(L_{i'm})}{F_{i'a}{}'(L_{i'a})} \tag{14}$$

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

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$$L_{im} \gtreqless L_{ia} \quad iff \quad \frac{A_{i'a}}{A_{i'm}} \gtreqless \frac{A_{ia}}{A_{im}} \tag{15}$$

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)
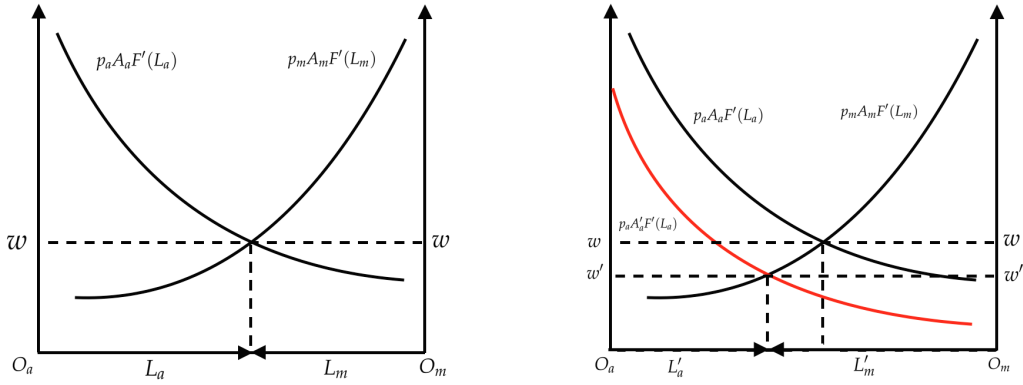
In the case of costly trade, firms (farms) will engage in arbitrage opportunities as before; however, the local price is bounded by a trade cost δ. A trader will engage in arbitrage, selling on the global market, as long as the global price is greater than the local price net of trade costs, i.e., $\bar{p}_j/\delta > p_j^A$. 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.[4] 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

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[4]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				
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				
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*** (0.0157)	0.00727 (0.00607)	0.0317*** (0.00998)	0.0191** (0.00782)	0.00406 (0.00296)
MONSOON RAINFALL (100mm)	-0.00116 (0.00249)	-0.000141 (0.00129)	-0.000329 (0.00173)	0.00183 (0.00128)	-0.000203 (0.000588)
FIXED EFFECTS	DISTRICT, YEAR, 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 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				
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	-0.000600	-0.00233	0.000631	-0.000459
	(0.00227)	(0.00111)	(0.00163)	(0.00114)	(0.000533)
FIXED EFFECTS	DISTRICT, YEAR, 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 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				
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) $t_L = 23, t_H = \infty$	0.00178 (0.00182)	-0.000908 (0.00247)	-0.0000676 (0.00173)	0.00144 (0.00152)
DEGREE DAYS (10 days) $t_L = 0, t_H = 23$	-0.0117*** (0.00364)	-0.00665** (0.00281)	-0.00215 (0.00218)	-0.000371 (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
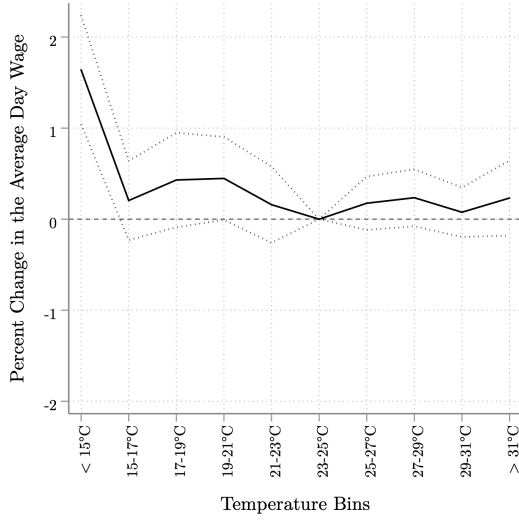
(a) Agriculture
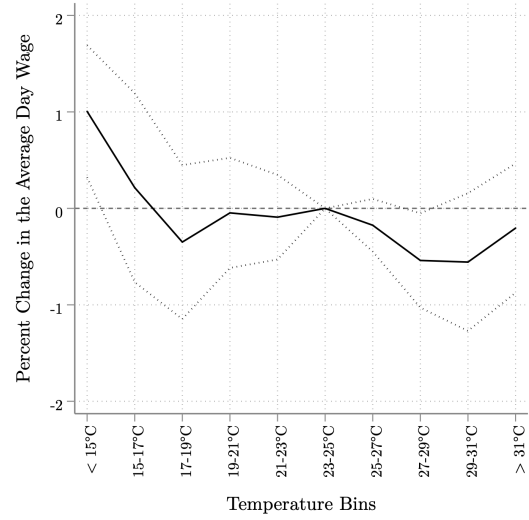
(b) Manufacturing
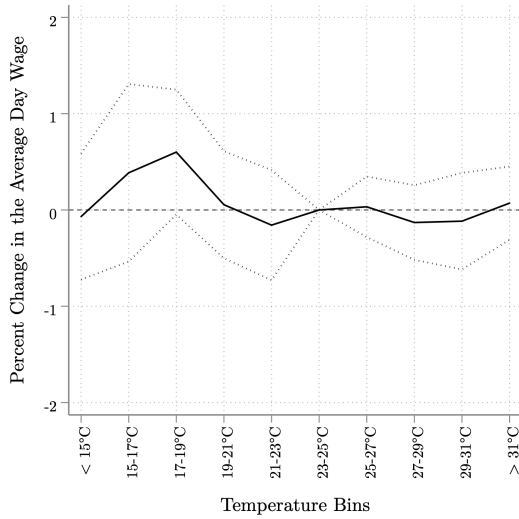
(c) Services
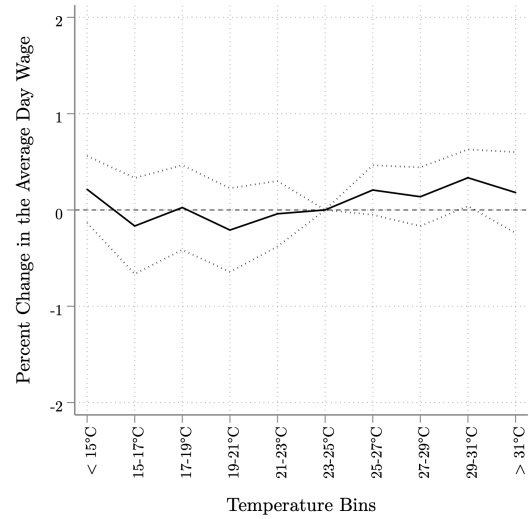
(d) Construction

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) $t_L = 23, t_H = \infty$	-0.00154** (0.000632)	0.000697** (0.000325)	0.000346 (0.000335)	0.0000367 (0.000235)	-0.0000134 (0.00000978)
DEGREE DAYS (10 days) $t_L = 0, t_H = 23$	-0.00266*** (0.000641)	0.000321 (0.000305)	0.00181*** (0.000373)	0.000231 (0.000321)	0.0000413 (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
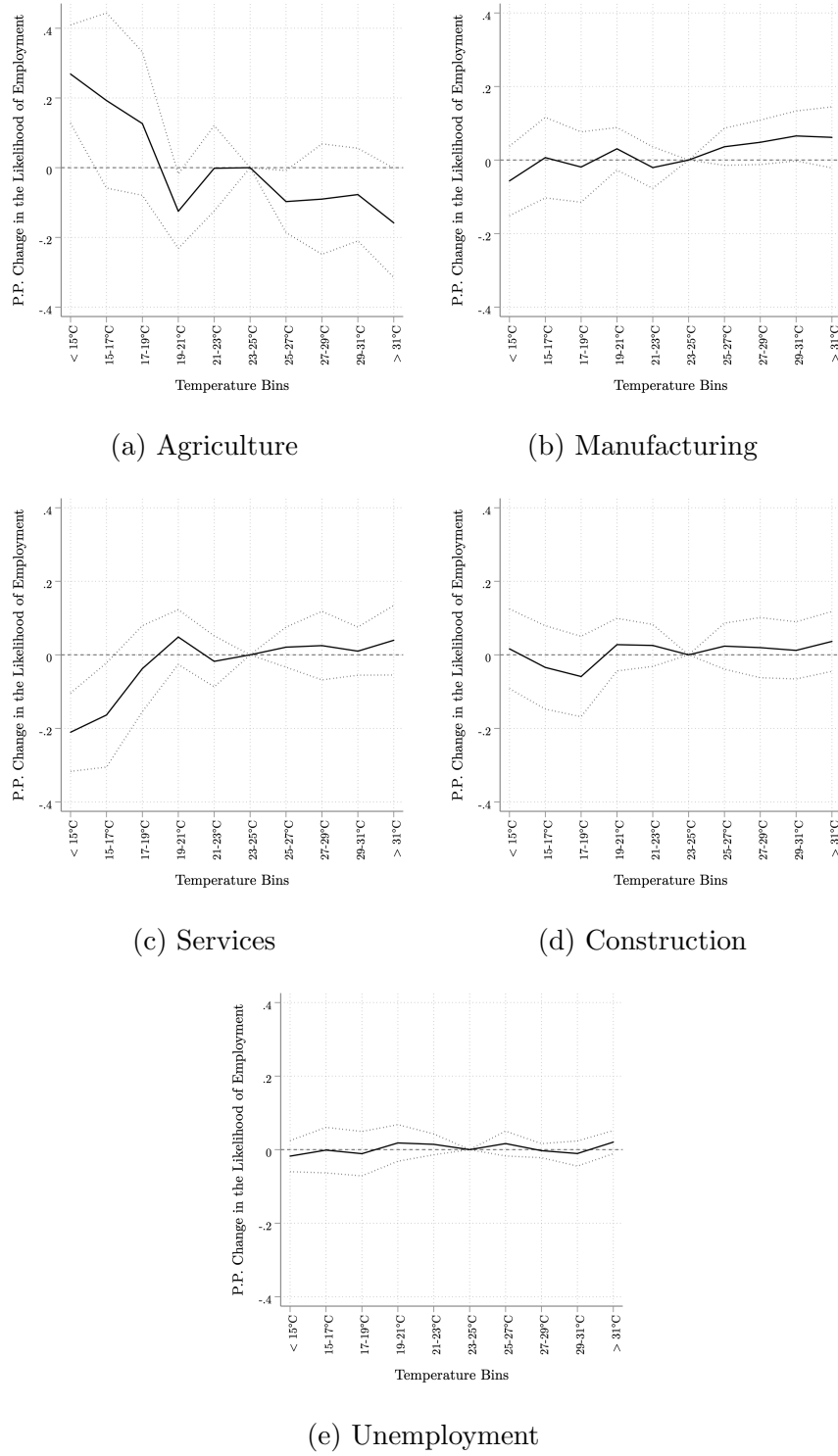
(a) Agriculture

(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	-0.134**	-0.120*	-0.0348	0.0238
TEMPERATURE (°C)	(0.0538)	(0.0676)	(0.0532)	(0.0431)
1-YEAR LAG	No	No	No	No
1-YEAR LEAD	No	No	No	No
DAILY AVERAGE	-0.107**	-0.0850	-0.0274	0.0183
TEMPERATURE (°C)	(0.0435)	(0.0809)	(0.0413)	(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. The first row of results are the main results from Table 2, without controls for lags and leads. 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	-0.0714***	0.0204**	0.0335***	0.0105	0.00700*
TEMPERATURE (°C)	(0.0165)	(0.00867)	(0.00953)	(0.00673)	(0.00370)
1-YEAR LAG	No	No	No	No	No
1-YEAR LEAD	No	No	No	No	No
DAILY AVERAGE	-0.0664***	0.0198***	0.0291***	0.0114**	-0.00417*
TEMPERATURE (°C)	(0.0169)	(0.00744)	(0.00865)	(0.00540)	(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				
OBSERVATIONS	1,062	1,062	1,062	1,062	1,062

NOTES: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. The first row of results are the main results from Table 3, without controls for lags and leads. 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:

$$
\hat{m}_{od} = \begin{cases} m_{od} & \text{if } \ell_o = \ell_d \\[2em] \dfrac{\sum_{\ell_o \neq \ell_d \in S_d} M_{do}}{\sum_{S_d} \sum_{\ell_o \neq \ell_d \in S_d} M_{do}} \sum_{\ell_d \neq \ell_o \in S_o} m_{od} & \text{if } \ell_o \neq \ell_d \text{ and } S_o = S_d \\[2em] \dfrac{\sum_{S_o \neq S_d} \sum_{\ell_o \neq \ell_d \in S_o} M_{do}}{\sum_{S_d} \sum_{S_o \neq S_d} \sum_{\ell_o \neq \ell_d \in S_o} M_{do}} \sum_{S_d \neq S_o} \sum_{\ell_d \neq \ell_o \in S_d} m_{od} & \text{if } \ell_o \neq \ell_d \text{ and } S_o \neq S_d \end{cases}
$$

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.[5] In the case that all migration is spread equally between all districts, each

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[5]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.[6] 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.

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[6] -0.000669 × 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	-0.0878***	0.0228*	0.0368***	0.0168	-0.00502
TEMPERATURE (°C)	(0.0234)	(0.0120)	(0.0115)	(0.0120)	(0.00416)
MONSOON RAINFALL (100mm)	-0.00405	0.00151	-0.00122	0.00259	-0.0000648
(100 mm)	(0.00366)	(0.00168)	(0.00200)	(0.00170)	(0.000471)
DAT ×	0.00258	-0.000375	-0.000570	-0.000938	0.000381
MIGRANT SHARE	(0.00193)	(0.00125)	(0.000937)	(0.00176)	(0.000364)
MONSOON RAINFALL	0.0000613	-0.0000215	0.000287***	-0.000296	0.0000183
× MIGRANT SHARE	(0.000277)	(0.000126)	(0.0000992)	(0.000185)	(0.0000294)
FIXED EFFECTS	DISTRICT, YEAR, 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 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	-0.0689***	0.0212**	0.0315***	0.0105	0.00569
TEMPERATURE (°C)	(0.0174)	(0.00949)	(0.0102)	(0.00650)	(0.00402)
LOCAL MONSOON RAINFALL	-0.00333	0.00111	0.000535	0.000661	0.00102*
(100 mm)	(0.00242)	(0.00123)	(0.00171)	(0.00121)	(0.000536)
FOREIGN DAILY AVERAGE	-0.000669	9.01e-08	0.000600	-0.000131	0.000200
TEMPERATURE (°C)	(0.000811)	(0.000342)	(0.000446)	(0.000329)	(0.000160)
FOREIGN MONSOON RAINFALL	-0.000924	0.000533	0.00101	-0.000551	-0.0000670
(100 mm)	(0.00108)	(0.000621)	(0.000780)	(0.000549)	(0.000202)
FIXED EFFECTS	DISTRICT, YEAR, 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 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.[7] 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.[8] 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.

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

[8]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	-0.111**	-0.113**	-0.00256
TEMPERATURE (°C)	(0.0447)	(0.0401)	(0.0189)
TEMPERATURE	-0.00977	-0.00829	0.00148
× FLEXIBLE	(0.0501)	(0.0441)	(0.0277)
MONSOON	0.000293	-0.00219	-0.00248
RAINFALL (100mm)	(0.00375)	(0.00640)	(0.00388)
RAINFALL	0.0139*	0.0152**	0.00126
× FLEXIBLE	(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
$\Theta(\tau_u = 0, \frac{\partial n_r}{\partial temperature} > 0)$	$0 < \frac{\partial n_{u,Flexible}}{\partial temperature} < \frac{\partial n_{u,Rigid}}{\partial temperature}$	$0 < \frac{\partial n_{r,Rigid}}{\partial temperature} < \frac{\partial n_{r,Flexible}}{\partial temperature}$
$\Theta(\tau_u = 0, \frac{\partial n_r}{\partial temperature} = 0)$	$0 < \frac{\partial n_{u,Rigid}}{\partial temperature} = \frac{\partial n_{u,Flexible}}{\partial temperature}$	$0 = \frac{\partial n_{r,Rigid}}{\partial temperature} = \frac{\partial n_{r,Flexible}}{\partial temperature}$
$\Theta(\tau_u > 0, \frac{\partial n_r}{\partial temperature} > 0)$	$0 < \frac{\partial n_{u,Rigid}}{\partial temperature} \overset{\leq}{>} \frac{\partial n_{u,Flexible}}{\partial temperature}$	$0 < \frac{\partial n_{r,Rigid}}{\partial temperature} < \frac{\partial n_{r,Flexible}}{\partial temperature}$
$\Theta(\tau_u > 0, \frac{\partial n_r}{\partial temperature} = 0)$	$0 < \frac{\partial n_{u,Rigid}}{\partial temperature} < \frac{\partial n_{u,Flexible}}{\partial temperature}$	$0 = \frac{\partial n_{r,Rigid}}{\partial temperature} = \frac{\partial n_{r,Flexible}}{\partial temperature}$

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.[9] 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 $\exp(\beta)$.

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[9]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*** (0.0199)	-0.193*** (0.0480)	-0.0672 (0.0705)	-0.00497 (0.0121)	-0.0690*** (0.00691)
TEMPERATURE × FLEXIBLE	0.136*** (0.0260)	0.152** (0.0528)	0.0402 (0.0648)	-0.0464* (0.0228)	0.0716*** (0.0228)
Panel B: Ordinal Ranking					
DAILY AVERAGE TEMPERATURE (°C)	-0.138*** (0.0406)	-0.165*** (0.0373)	-0.0474 (0.0635)	-0.00482 (0.0203)	-0.0405 (0.0277)
TEMPERATURE × FLEXIBLE	0.132** (0.0571)	0.180*** (0.0519)	0.0167 (0.0835)	-0.0747*** (0.0235)	0.0474 (0.0282)
Panel C: Cardinal Ranking					
DAILY AVERAGE TEMPERATURE (°C)	-0.214*** (0.0353)	-0.283*** (0.0462)	-0.0294 (0.101)	0.0216 (0.0324)	-0.0705** (0.0261)
TEMPERATURE × FLEXIBLE	0.235*** (0.0460)	0.338*** (0.0781)	-0.0177 (0.131)	-0.101* (0.0558)	0.0894* (0.0443)
Panel D: Separate Categories					
DAILY AVERAGE TEMPERATURE (°C)	-0.173*** (0.0200)	-0.192*** (0.0486)	-0.0663 (0.0710)	-0.00652 (0.0110)	-0.0703*** (0.00670)
TEMPERATURE × NEUTRAL	0.144*** (0.0362)	0.145** (0.0589)	0.0520 (0.0667)	-0.0341 (0.0254)	0.0896*** (0.0281)
TEMPERATURE × FLEXIBLE	0.114*** (0.0362)	0.158*** (0.0541)	-0.00626 (0.0657)	-0.0782** (0.0289)	0.0376** (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 × FLEXIBLE: γ_2	0.110 (0.0700)	0.249** (0.0967)	0.0598 (0.0429)	-0.0625* (0.0312)	0.0442* (0.0248)
TEMPERATURE × 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 × FLEXIBLE × 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 × District × Regulatory Group and Sector × Year × Regulatory Group				
OTHER CONTROLS	Monsoon Rainfall (including interactions) and Linear State × 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 × 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 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*** (0.0234)	-0.155*** (0.0462)	-0.0532 (0.0705)	0.00571 (0.0106)	-0.0575*** (0.00786)
Temperature × Flexible: γ_2	0.102** (0.0360)	0.146** (0.0599)	0.0390 (0.0651)	-0.0595** (0.0265)	0.0617** (0.0222)
Temperature × Below Threshold: γ_3	0.146*** (0.0317)	0.180* (0.0977)	0.0998 (0.0737)	0.00991 (0.0379)	0.0545*** (0.0135)
Temperature × Flexible × Below Threshold: γ_4	-0.0946** (0.0412)	-0.268** (0.119)	-0.0841 (0.0778)	0.0472 (0.0401)	-0.0395 (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** (0.0360)	0.146** (0.0599)	0.0390 (0.0651)	-0.0595** (0.0265)	0.0617** (0.0222)
Difference Below Threshold: $H_0 : \gamma_2 + \gamma_4 = 0$	0.007 (0.041)	-0.122 (0.111)	-0.045 (0.033)	-0.012 (0.036)	0.022 (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	-0.138***	-0.133**	-0.0839	0.00629	-0.0895***
TEMPERATURE (°C): γ_1	(0.0247)	(0.0467)	(0.0711)	(0.0114)	(0.00938)
TEMPERATURE	0.121***	0.141**	0.0685	-0.0579**	0.0951***
× FLEXIBLE: γ_2	(0.0334)	(0.0604)	(0.0668)	(0.0266)	(0.0213)
TEMPERATURE	0.166***	0.179*	0.118	0.0133	0.0766***
× BELOW THRESHOLD: γ_3	(0.0323)	(0.0995)	(0.0749)	(0.0363)	(0.0133)
TEMPERATURE × FLEXIBLE	-0.121***	-0.269**	-0.110	0.0409	-0.0695**
× BELOW THRESHOLD: γ_4	(0.0404)	(0.123)	(0.0780)	(0.0382)	(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	0.121***	0.141**	0.0685	-0.0579**	0.0951***
$H_0 : \gamma_2 = 0$	(0.0334)	(0.0604)	(0.0668)	(0.0266)	(0.0213)
Difference Below Threshold:	0.001	-0.128	-0.041	-0.017	0.026
$H_0 : \gamma_2 + \gamma_4 = 0$	(0.042)	(0.112)	(0.031)	(0.036)	(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*** (0.00152)	-0.00490*** (0.00124)	-0.00290 (0.00204)	-0.000722 (0.000558)	-0.00257*** (0.000500)
DD High × Flexible	0.00481*** (0.00128)	0.00520*** (0.00172)	0.00186 (0.00179)	0.000144 (0.000550)	0.00218*** (0.000631)
Degree Days (10 days) $t_L = 0, t_H = 17$	-0.00161 (0.00224)	-0.00429 (0.00578)	0.000359 (0.00102)	0.00156* (0.000864)	-0.000155 (0.000934)
DD Low × Flexible	0.00109 (0.00312)	0.000227 (0.00621)	-0.000606 (0.00169)	-0.00446** (0.00161)	0.000953 (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).
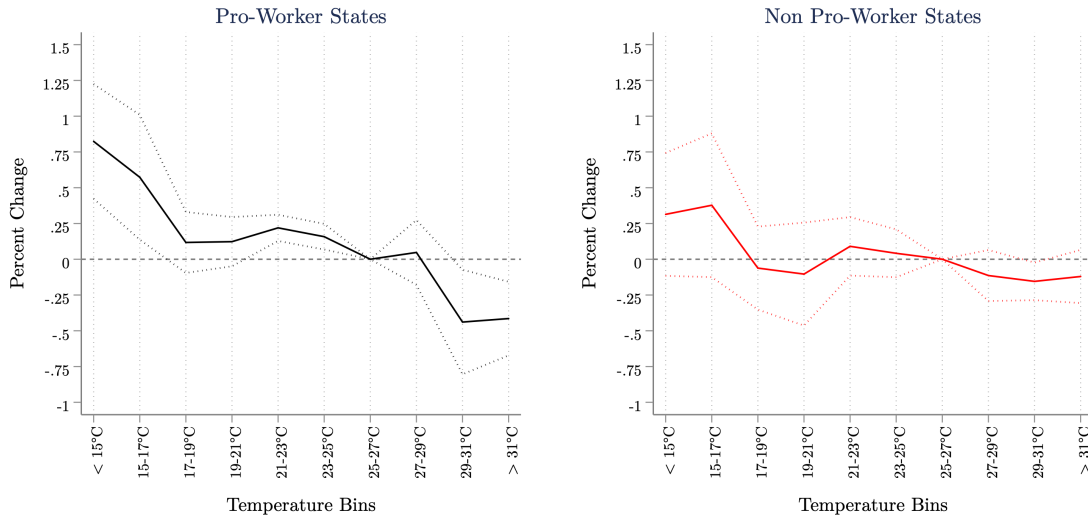
Figure D1: The Differential Effect of Temperature on Total Output

Notes: Standard errors are clustered at the state level.

Figure D2: The Differential Effect of Temperature on the Number of Contract Workers
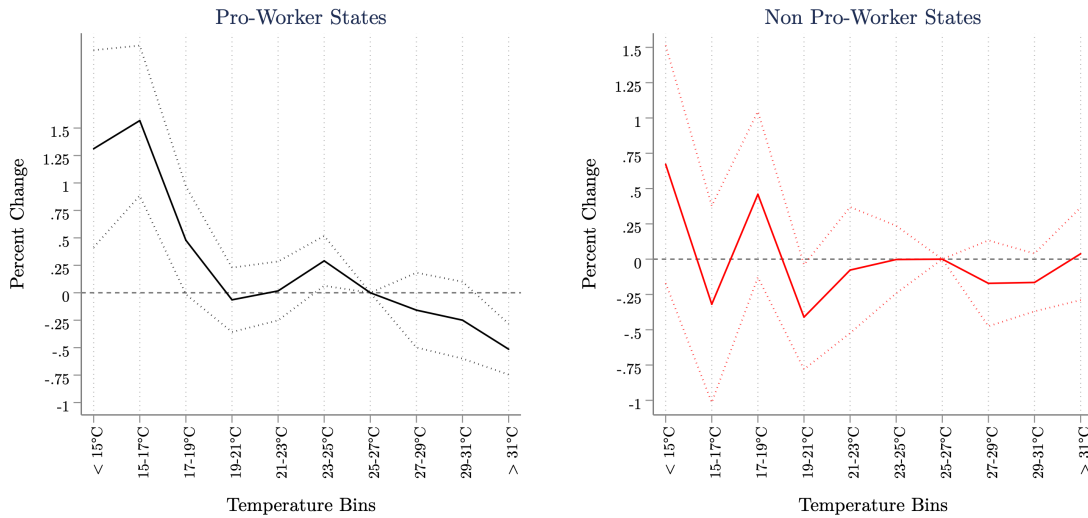
Notes: Standard errors are clustered at the state level.

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

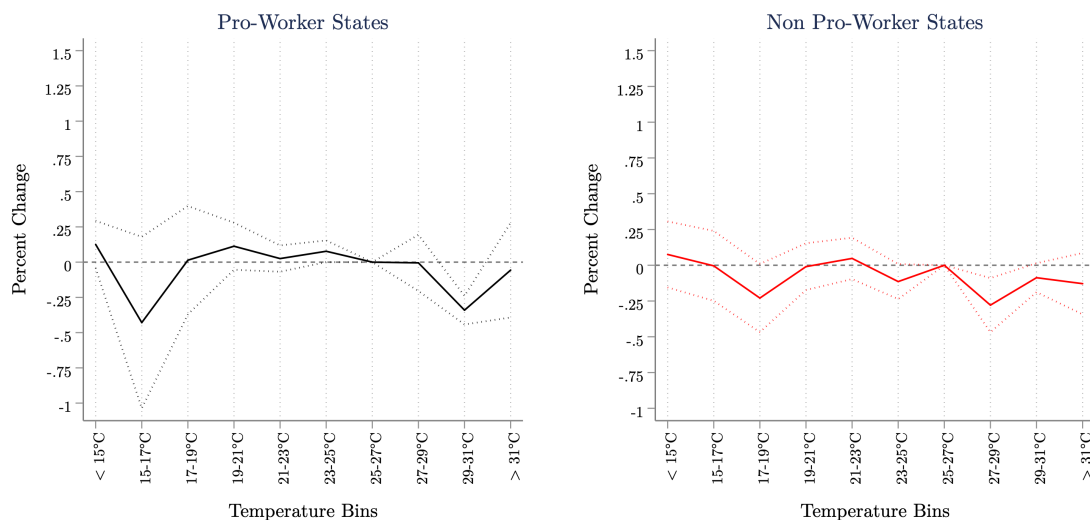Notes: Standard errors are clustered at the state level.

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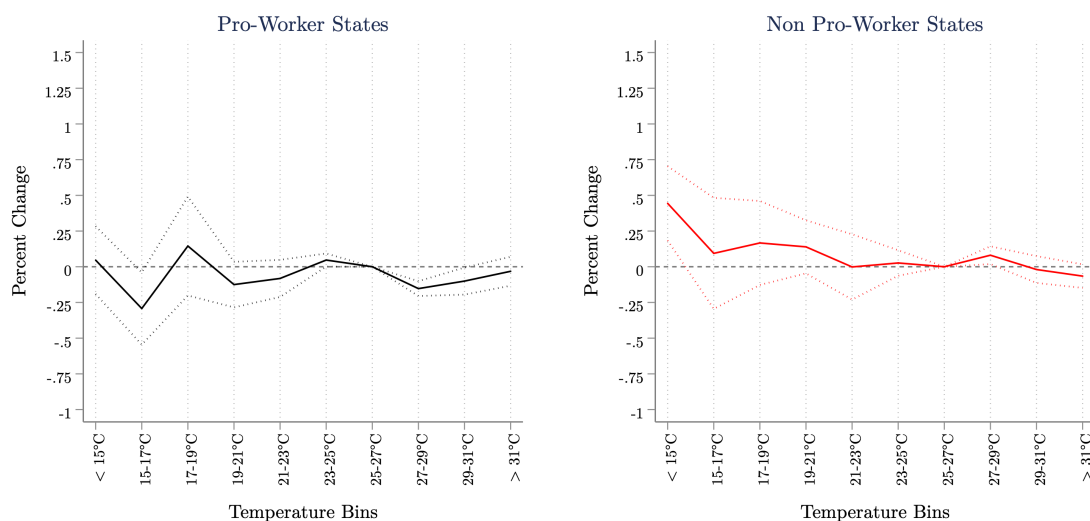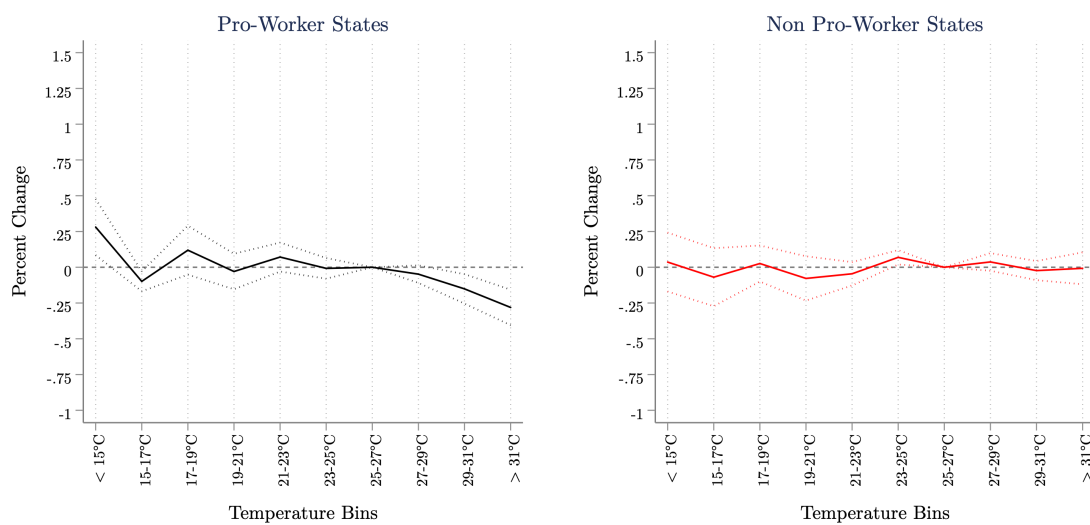

Notes: Standard errors are clustered at the state level.

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	-0.173***	-0.193***	-0.0672	-0.00497	-0.0690***
TEMPERATURE (°C)	(0.0199)	(0.0480)	(0.0705)	(0.0121)	(0.00691)
TEMPERATURE	0.136***	0.152**	0.0402	-0.0464*	0.0716***
× FLEXIBLE	(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	-0.171***	-0.159***	-0.0646	0.0000346	-0.0612***
TEMPERATURE (°C)	(0.0233)	(0.0536)	(0.0469)	(0.0134)	(0.00919)
TEMPERATURE	0.136***	0.136**	0.0340	-0.0616***	0.0642***
× FLEXIBLE	(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*** (0.0199)	-0.193*** (0.0480)	-0.0672 (0.0705)	-0.00497 (0.0121)	-0.0690*** (0.00691)
Temperature × Flexible	0.136*** (0.0260)	0.152** (0.0528)	0.0402 (0.0648)	-0.0464* (0.0228)	0.0716*** (0.0228)
Panel B: Temperature (No Rainfall Controls)					
Daily Average Temperature (°C)	-0.114*** (0.0217)	-0.152** (0.0604)	-0.0528 (0.0549)	0.0217 (0.0188)	-0.0498*** (0.00796)
Temperature × Flexible	0.0914*** (0.0271)	0.131** (0.0586)	0.0200 (0.0520)	-0.0545** (0.0243)	0.0534*** (0.0181)
Panel C: Rainfall (Controlling for Temperature)					
Monsoon Rainfall (100mm)	-0.0180*** (0.00619)	-0.0130 (0.00959)	-0.00478 (0.00702)	-0.00814 (0.00579)	-0.00606*** (0.000833)
Rainfall × Flexible	0.0135** (0.00563)	0.00487 (0.0110)	0.00652 (0.00671)	0.000870 (0.00640)	0.00569* (0.00271)
Panel D: Rainfall (No Temperature Controls)					
Monsoon Rainfall (100mm)	-0.00745 (0.00538)	0.00217 (0.0128)	-0.000706 (0.00262)	-0.00803 (0.00552)	-0.00178** (0.000637)
Rainfall × Flexible	0.00564 (0.00517)	-0.00635 (0.0131)	0.00424 (0.00330)	0.00440 (0.00589)	0.00142 (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 (0.0811)	-0.112 (0.0730)	-0.0869 (0.0746)	-0.0142 (0.0186)	-0.0640*** (0.00945)
TEMPERATURE × FLEXIBLE	0.0497 (0.0807)	0.120* (0.0634)	0.0612 (0.0693)	-0.0555*** (0.0181)	0.0458*** (0.0125)
Panel B: Temperature (No Rainfall Controls)					
DAILY AVERAGE TEMPERATURE (°C)	-0.0664** (0.0298)	-0.199** (0.0765)	-0.0147 (0.0723)	0.00214 (0.0179)	-0.0428*** (0.0125)
TEMPERATURE × FLEXIBLE	0.0235 (0.0368)	0.189*** (0.0636)	-0.0204 (0.0698)	-0.0658*** (0.0160)	0.0279** (0.0129)
Panel C: Rainfall (Controlling for Temperature)					
MONSOON RAINFALL (100mm)	-0.0104 (0.0125)	0.0161*** (0.00303)	-0.0137*** (0.00163)	-0.00324** (0.00134)	-0.00429* (0.00215)
RAINFALL × FLEXIBLE	0.00340 (0.0125)	-0.0117* (0.00563)	0.0178*** (0.00188)	0.00133 (0.00191)	0.00342 (0.00230)
Panel D: Rainfall (No Temperature Controls)					
MONSOON RAINFALL (100mm)	-0.00440 (0.00867)	0.0223*** (0.00529)	-0.00911** (0.00374)	-0.00244 (0.00143)	-0.000905 (0.00227)
RAINFALL × FLEXIBLE	-0.000230 (0.00834)	-0.0190*** (0.00527)	0.0140*** (0.00430)	0.00369** (0.00164)	0.000558 (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.

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

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 im-

perfect 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.

$$\sigma \propto \frac{\partial \log w_m^p}{\partial Temperature} / \frac{\partial \log L_m^c}{\partial Temperature} = \frac{\partial \log w_m^p}{\partial \log L_m^c} = 0.436 \tag{16}$$

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 (0.0469)	-0.0734*** (0.0227)	-0.0736*** (0.0239)
Temperature × Flexible: γ_2	0.0546 (0.0551)	0.0536** (0.0253)	0.0545* (0.0262)
Temperature × Below Threshold: γ_3	0.0278 (0.0485)	0.0638* (0.0354)	0.0646 (0.0377)
Temperature × Flexible × Below Threshold: γ_4	0.0360 (0.0612)	-0.0553 (0.0397)	-0.0582 (0.0425)
Formal Tests			
Difference Above Threshold: $H_0 : \gamma_2 = 0$	0.0546 (0.0535)	0.0536** (0.0253)	0.0545* (0.0262)
Difference Below Threshold: $H_0 : \gamma_2 + \gamma_4 = 0$	0.090 (0.058)	-0.002 (0.029)	-0.003 (0.030)
Sector × District Fixed Effects	Yes	Yes	Yes
Sector × 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 × 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.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 17 presents the empirical specification for this research design,

$$
\begin{aligned}
\log Y_{ijrdst} \; = \; & \gamma_1 f(w_{dt}) + \gamma_2 f(w_{dt}) \times \text{FLEXIBLE}_s \\
& + \gamma_3 f(w_{dt}) \times \text{BELOW}_r + \; \gamma_4 f(w_{dt}) \times \text{BELOW}_r \times \text{FLEXIBLE}_s \\
& + \delta_1 \text{BELOW}_r + \delta_2 \text{BELOW}_r \times \text{FLEXIBLE}_s + \delta_3 f(\text{FIRM SIZE}_{ijdt}) \\
& + \delta_4 f(\text{FIRM SIZE}_{ijdt}) \times f(w_{dt}) + \delta_5 f(\text{FIRM SIZE}_{ijdt}) \times \text{FLEXIBLE}_s \\
& + \delta_6 f(\text{FIRM SIZE}_{ijdt}) \times f(w_{dt}) \times \text{FLEXIBLE}_s \\
& + \alpha_{jd} + \alpha_{jt} + \phi_s t + \varepsilon_{ijdt}.
\end{aligned}
\tag{17}
$$

Equation 17 is similar in essence to equation ??, 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, BELOW_r, and include the interaction of this variable with the labor regulation environment, $\text{BELOW}_r \times \text{FLEXIBLE}_s$. 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*** (0.0446)	-0.296*** (0.0917)	0.00147 (0.0102)	-0.00217 (0.0282)	-0.0444*** (0.0143)
TEMPERATURE × FLEXIBLE: γ_2	0.151** (0.0545)	0.275** (0.108)	-0.0139 (0.0185)	0.0108 (0.0398)	0.0686** (0.0277)
TEMPERATURE × BELOW THRESHOLD: γ_3	0.0307*** (0.0102)	0.135*** (0.0385)	0.00969 (0.0128)	0.00216 (0.0102)	0.00799 (0.00916)
TEMPERATURE × FLEXIBLE × BELOW THRESHOLD: γ_4	-0.0248* (0.0134)	-0.124*** (0.0412)	-0.00994 (0.0135)	-0.000425 (0.0120)	0.00323 (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*** (0.0102)	0.135*** (0.0385)	0.00969 (0.0128)	0.00216 (0.0102)	0.00799 (0.00916)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	0.005 (0.008)	0.011 (0.011)	-0.000 (0.005)	0.002 (0.004)	0.011** (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 (0.0733)	-0.0722*** (0.0166)	-0.0714*** (0.0162)
TEMPERATURE × FLEXIBLE: γ_2	0.141* (0.0712)	0.0533 (0.0325)	0.0507 (0.0328)
TEMPERATURE × BELOW THRESHOLD: γ_3	0.0195** (0.00751)	0.0101 (0.00725)	0.00921 (0.00665)
TEMPERATURE × FLEXIBLE × BELOW THRESHOLD: γ_4	-0.0221** (0.0102)	-0.0127 (0.0109)	-0.0123 (0.0106)
SECTOR × DISTRICT FIXED EFFECTS	Yes	Yes	Yes
SECTOR × YEAR FIXED EFFECTS	Yes	Yes	Yes
RAINFALL CONTROLS	Yes	Yes	Yes
STATE × 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** (0.00751)	0.0101 (0.00725)	0.00921 (0.00665)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	-0.002 (0.008)	-0.002 (0.007)	-0.003 (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.[10] 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 Mc-Crary 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

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[10]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.[11] 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.

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[11] 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.
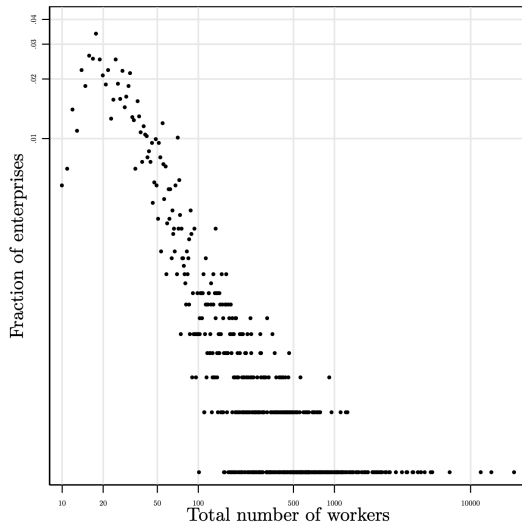
Figure D6: The Firm-Size Distribution
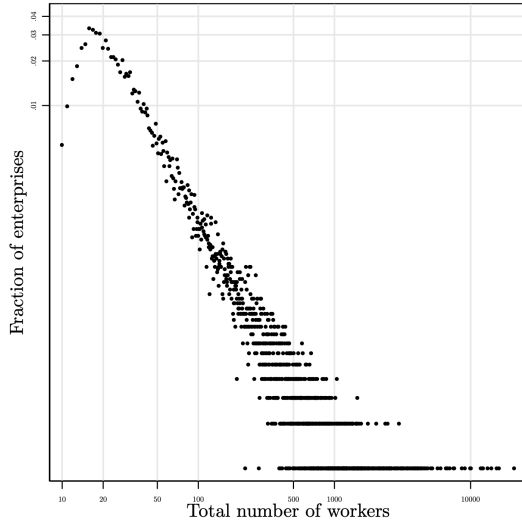
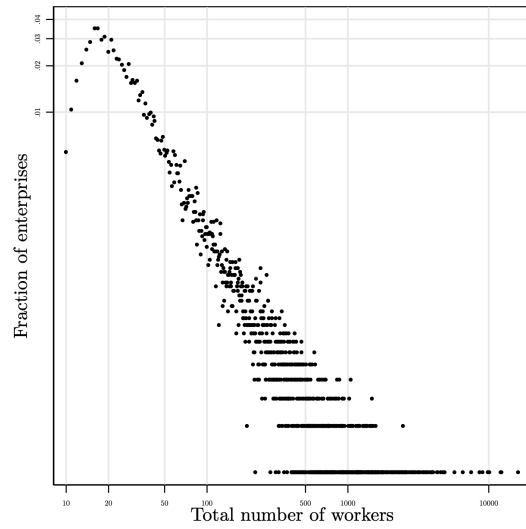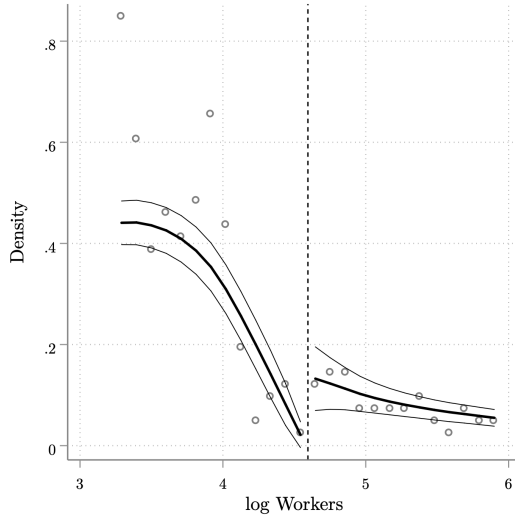(a) All States
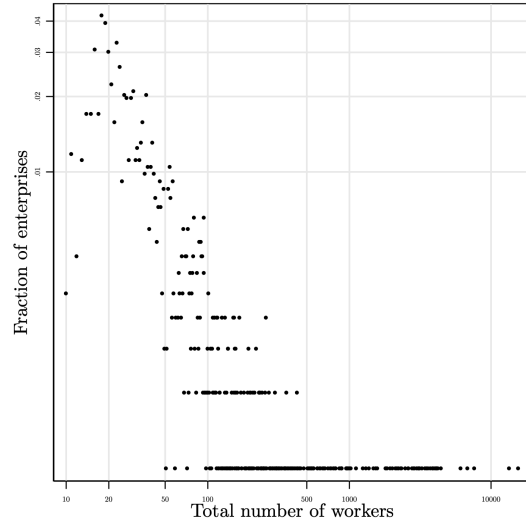
(b) West Bengal (Pro-Worker)

(c) Other Pro-Worker States

(d) Non Pro-Worker States

Figure D7: Formal Bunching Tests

(a) Pro-Worker (Threshold = 100)
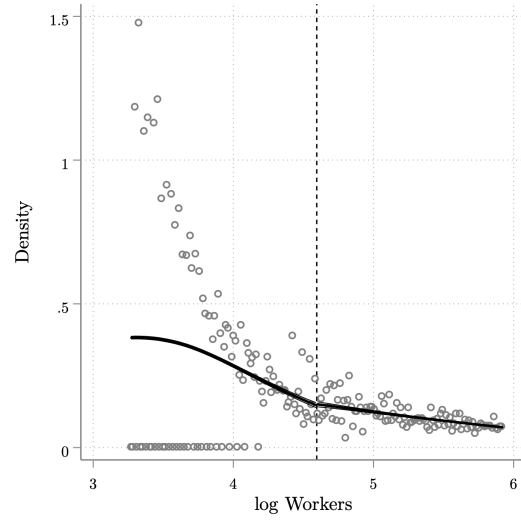
(b) Not Pro-Worker (Threshold = 100)
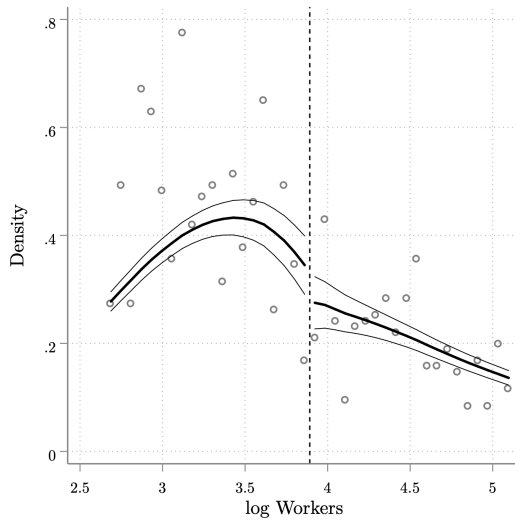
(c) West Bengal (Threshold = 50)
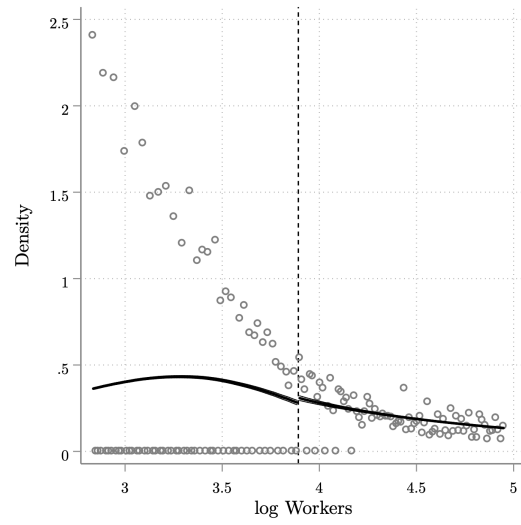
(d) Not West Bengal (Threshold = 50)

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 (0.0152)	-0.00555 (0.0170)	-0.0668 (0.237)	-0.148 (0.235)
TEMPERATURE × FLEXIBLE		-0.0110 (0.00875)		0.0877 (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*** (0.0487)	-0.286*** (0.0853)	0.0000343 (0.00934)	-0.0112 (0.0320)	-0.0505*** (0.0132)
TEMPERATURE × FLEXIBLE: γ_2	0.150** (0.0546)	0.236** (0.106)	-0.0138 (0.0189)	0.00593 (0.0431)	0.0700** (0.0273)
TEMPERATURE × BELOW THRESHOLD: γ_3	0.0403** (0.0155)	0.129* (0.0644)	0.00419 (0.0165)	0.00597 (0.0151)	0.00969 (0.00668)
TEMPERATURE × FLEXIBLE × BELOW THRESHOLD: γ_4	-0.0118 (0.0131)	-0.115* (0.0614)	-0.00854 (0.0160)	0.000980 (0.0162)	0.00527 (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** (0.0155)	0.129* (0.0644)	0.00419 (0.0165)	0.00597 (0.0151)	0.00969 (0.00668)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	0.028*** (0.008)	0.014 (0.016)	-0.004 (0.005)	0.007 (0.006)	0.015** (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** (0.0511)	-0.218** (0.101)	-0.0204** (0.00878)	-0.00371 (0.0198)	-0.0330 (0.0193)
TEMPERATURE × FLEXIBLE: γ_2	0.0968 (0.0611)	0.160 (0.124)	0.0137 (0.0173)	-0.0116 (0.0402)	0.0360 (0.0273)
TEMPERATURE × BELOW THRESHOLD: γ_3	0.00869 (0.0178)	0.132** (0.0581)	0.00683 (0.00457)	-0.0135* (0.00655)	-0.00610 (0.00603)
TEMPERATURE × FLEXIBLE × BELOW THRESHOLD: γ_4	-0.00494 (0.0187)	-0.124* (0.0598)	-0.0104 (0.00603)	0.0192* (0.00978)	0.0166* (0.00815)
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	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 (0.0178)	0.132** (0.0581)	0.00683 (0.00457)	-0.0135* (0.00655)	-0.00610 (0.00603)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	0.004 (0.006)	0.008 (0.011)	-0.004 (0.004)	0.006 (0.007)	0.011* (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** (0.0498)	-0.333*** (0.0891)	0.00535 (0.0152)	0.000106 (0.0338)	-0.0385*** (0.0116)
TEMPERATURE × FLEXIBLE: γ_2	0.126** (0.0544)	0.325** (0.120)	-0.0163 (0.0212)	0.00810 (0.0441)	0.0671** (0.0282)
TEMPERATURE × BELOW THRESHOLD: γ_3	0.0291*** (0.00933)	0.139*** (0.0451)	0.00883 (0.0170)	0.00745 (0.0125)	0.0123 (0.00968)
TEMPERATURE × FLEXIBLE × BELOW THRESHOLD: γ_4	-0.0189 (0.0133)	-0.130** (0.0485)	-0.00972 (0.0175)	-0.00339 (0.0147)	-0.000116 (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*** (0.00933)	0.139*** (0.0451)	0.00883 (0.0170)	0.00745 (0.0125)	0.0123 (0.00968)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	0.010 (0.009)	0.008 (0.012)	-0.000 (0.004)	0.004 (0.005)	0.021** (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 (0.0980)	-0.265*** (0.0841)	0.00826 (0.0485)	0.0247 (0.0518)	-0.0208 (0.0252)
Temperature × Flexible: γ_2	0.0629 (0.0948)	0.306 (0.177)	-0.0483 (0.0417)	0.0154 (0.0612)	0.0504 (0.0453)
Temperature × Below Threshold: γ_3	-0.00290 (0.00550)	0.0502 (0.0589)	0.0111 (0.0243)	0.0532 (0.0336)	0.0115** (0.00421)
Temperature × Flexible × Below Threshold: γ_4	0.0597** (0.0221)	-0.0249 (0.0678)	-0.0151 (0.0256)	-0.0537 (0.0375)	0.00464 (0.00648)
Fixed Effects	Sector × District & Sector × Year				
Other Controls	Monsoon Rainfall (inc. interactions), Linear State × 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 (0.00550)	0.0502 (0.0589)	0.0111 (0.0243)	0.0532 (0.0336)	0.0115** (0.00421)
Discontinuity (Non Pro-Worker): $H_0 : \gamma_3 + \gamma_4 = 0$	0.056** (0.020)	0.025 (0.032)	-0.003 (0.008)	-0.000 (0.001)	0.016** (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).