Weather, Labor Reallocation, and Industrial Production: Evidence from India.*

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Abstract

Temperature-driven reductions in the demand for agricultural labor are associated with increases in the share of workers engaged in manufacturing, suggesting that the ability of non-agricultural sectors to absorb workers may play a key role in attenuating the economic consequences of weather-driven changes in agricultural productivity. Exploiting firm-level variation in the propensity to absorb these workers, I find that this reallocation is associated with relative expansions in manufacturing activity in flexible labor market environments. Counterfactual estimates suggest that in the absence of labor reallocation the aggregate consequences of temperature increases would be up to 40% higher.

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1 Introduction

Understanding the relationship between economic and natural systems is of central importance, especially in developing countries given the role that agriculture plays for the economic lives of the poor. One relationship that has received particular attention in recent years is the relationship between weather and economic activity. However, less is known about how economic agents respond to weather, and the degree to which behavioral responses moderate the economic consequences of weather. One important margin is the degree to which agricultural workers are able to manage weather-driven changes in labor demand. Are workers able to find work in other sectors or locations, or do labor market frictions impede this reallocation, inextricably coupling the livelihoods and welfare of these workers to changes in the natural environment?

I seek to answer this question by combining worker-, firm- and district-level data with high-resolution meteorological data in India, exploring the effects of weather on agricultural productivity, industrial production and local labor market outcomes. First, and unsurprisingly, I identify that increases in temperature are associated with a reduction in agricultural production, and in turn the employment and wages of agricultural workers, demonstrating the important role that weather plays in driving short-run agricultural productivity, and the livelihoods of agricultural workers (Deaton, 1992, Paxson, 1992, Rosenzweig and Binswanger, 1993, Townsend, 1994, Jayachandran, 2006, Guiteras, 2009, Taraz, 2012, Kaur, 2014, Mobarak and Rosenzweig, 2014, Kala, 2015).

Having observed the negative effects of temperature increases on agricultural outcomes, it is important to understand what happens to workers in response to these changes. While I find that weather is a strong driver of short-run agricultural productivity, I observe that it has no effect on agricultural prices, consistent with a "law of one price", suggesting that reductions in agricultural productivity should push workers out of agriculture and into other tradable sectors of the economy (Burgess and Donaldson, 2010, 2012, Donaldson, 2015b); however, this depends on the ability of workers to move across sectors, and on the ability of other sectors to absorb these workers in response to short-run productivity shocks. Having shown that increases in temperature result in a reduction in the employment share of agriculture, I estimate a corresponding shift of labor into the manufacturing sector. In addition, I estimate that there are no changes in unemployment, or in the local population through migration, bounding local labor markets and suggesting that the main margin through which labor reallocation in India occurs is sectoral rather than spatial. These results suggest that the ability of non-agricultural sectors to absorb workers within local labor markets may play a key role in managing the economic consequences of weather-driven changes in agricul-

tural productivity, highlighting the importance of market integration and diversification can play in attenuating sectoral productivity shocks (Matsuyama, 1992, Foster and Rosenzweig, 2004, Jayachandran, 2006, Burgess and Donaldson, 2010, 2012, Autor et al., 2013, Bustos et al., 2015, Costinot et al., 2015, Donaldson, 2015a,b, Henderson et al., 2015, Hornbeck and Keskin, 2015, Hornbeck and Moretti, 2015, Mian and Sufi, 2015).

Having demonstrated that other sectors of the economy are major absorbers of labor in the face of weather-driven changes in agricultural productivity, it is of interest to understand what these workers do, and how they affect firm and incumbent worker outcomes when they move into the manufacturing sector. However, identifying these effects presents a number of empirical challenges. To interpret the effects of weather on manufacturing outcomes as being driven by labor reallocation, it is necessary that these outcomes are not affected by weather in any other way. This is a strong assumption, as there are potentially many channels through which weather could affect other sectors, directly and/or through agricultural linkages.[1] Consequently, any estimate of the relationship between weather and manufacturing outcomes will provide the net effect of all the competing and complementary channels involved. Given this ambiguity, it is difficult to interpret empirical estimates of weather in a meaningful way. Where empirically relevant channels move in the same direction, we fail to arrive at a meaningful economic interpretation. Where multiple channels are competing, specific effects may be missed entirely, or selected interpretations underestimated.

To try and address this concern, I exploit variation in the propensity of firms to absorb labor in response to transitory changes in labor demand, arising from year-to-year changes in the weather, helping to identify the channel of interest – the labor reallocation effect. To do this, I construct a firm-level measure of exposure to India's labor regulation environment that builds on Besley and Burgess (2004), who classify the rigidity of the labor

[1] Changes in agricultural productivity could affect manufacturing outcomes in sectors that use agricultural products as inputs, propagating shocks through intermediaries (Acemoglu et al., 2012), and a reduction in agricultural income could reduce the consumption base for manufactured products with local demand (Soderbom and Rijkers, 2013, Henderson et al., 2012, Santangelo, 2015, Emerick, 2016). Weather may also affect manufacturing production directly through its impact on factors of production. For example, an increase in temperature may reduce production through a reduction in the health or physical/cognitive ability of workers and managers, through an increase in absenteeism due to avoidance behaviour (Mackworth, 1946, 1947, Kenrick and McFarlane, 1986, Hsiang, 2010, Cachon et al., 2012, Adhvaryu et al., 2015, Burgess et al., 2014, Somonathan et al., 2015, Heal and Park, 2014, Graff Zivin and Neidell, 2014, Graff Zivin et al., 2015). Heavy rainfall may affect workers' ability to get to work (Bandiera et al., 2015b), disrupt supply chains. In addition, increased temperature, or a reduction in rainfall in areas dependent on hydroelectric power generation, is likely to put additional stress on an already fragile electricity infrastructure, reducing the supply of electrical power (Ryan, 2014, Alcott et al., 2015). Increases in temperature or reductions in rainfall may increase groundwater use, resulting in competition for water between agriculture and industry (Keskin, 2010). Finally, capital stocks and flows may be affected if weather affects capital depreciation, the relative productivity of inputs, or the level of investment in the economy if capital is locally constrained (Jina and Hsiang, 2015, Asher and Novosad, 2014).

market environment using state-level amendments to the Industrial Disputes Act of 1947 (hereafter IDA). In rigid labor market environments, firms face significant hiring and firing costs that, I argue, diminish the incentive to hire workers in response to transitory changes in the availability of labor (Oi, 1962, Nickell, 1978, Bentolila and Bertola, 1990, Hamermesh, 1993, Heckman, 2003, Besley and Burgess, 2004, Haltiwanger et al., 2008, Ahsan and Pagés, 2009, Adhvaryu et al., 2013, Amirapu and Gechter, 2014, Chaurey, 2015). By contrast, these costs are supposedly lower in more flexible labor market environments, where firms have more bargaining power over hiring decisions. However, this alone is not sufficient to identify the effects of labor reallocation. There may be other differences across space that could conflate the estimated effects of weather on manufacturing outcomes based on these differences. Consequently, I introduce firm-level exposure to the labor regulation environment, based on chapter 5b of the Industrial Disputes Act, which specifies the size that firms can reach before they are regulated under the IDA. In support of this identification strategy, I observe bunching in the firm-size distribution to the left of the regulatory threshold in rigid labor market environments, but not in the case of the flexible labor market environments, suggesting that the IDA has a binding effect on firm behavior.

For the identification strategy to have any viability the other effects of weather must not have a differential effect across across labor regulation environments. To test this I first examine the effects of temperature on unregulated firms. This provides a direct test for the assumption that the other channels of weather are not differential across labor regulation environments. In support of this assumption I estimate that there are limited differential effects of temperature on unregulated firms across labor regulation environments. While it would be a overtly strong to claim the absence of confounding factors, this suggests that, at a minimum, the net effect of other policy variation, heterogeneous weather effects and general equilibrium considerations cancel each other out across labor regulation environments. Further support for this premise is found by exploring the differential effects of temperature on unregulated sectors across labor regulation environments, where again I find limited evidence of spatial differences. Consequently, to the extent that these factors do exist, empirically they are likely to have a limited impact on the identification of the labor reallocation effect in regulated firms. Only confounding differences across labor regulation environments that differentially affect regulated firms, but not unregulated firms, will affect identification of the labor reallocation effect.

With this in mind, I next examine the effects of temperature on regulated firms. I estimate that, in rigid labor market environments, an increase in temperature is associated with a negative impact on firm performance, consistent with – but not limited to – an emerging literature that suggests that increases in temperature have significant effects on labor produc-

tivity through a drag on physiological and cognitive ability (Mackworth, 1946, 1947, Kenrick and McFarlane, 1986, Hsiang, 2010, Cachon et al., 2012, Adhvaryu et al., 2015, Somonathan et al., 2015, Heal and Park, 2014, Graff Zivin and Neidell, 2014, Graff Zivin et al., 2015). However, in flexible labor market environments, I estimate that firms experience a relative increase in employment and output, with new entrants moving into casual manufacturing activities. This expansion offsets the adverse effects of temperature. These effects provide support for the premise that firms in flexible labor market environments are more able to absorb workers in response to agricultural productivity shocks. In addition I estimate a relative increase in the average wage of permanent workers, manufacturing productivity (TFP and output per worker), and the number of items that the firm produces, suggesting that the activities that casual and permanent workers engage in are complementary to production.

The absence of movement into permanent positions suggests that labor markets can be characterised, at least in the short run, as dualistic: workers earn different wages depending on the type of employment activities in which they engage (casual vs. permanent).[2] These results are consistent with an emerging literature that explores the impact of agricultural productivity shocks on local economic activity (Hornbeck, 2012, Hornbeck and Naidu, 2014, Bustos et al., 2015, Henderson et al., 2015, Hornbeck and Keskin, 2015, Marden, 2015). However, most of the research to date has focused on long-run changes in agricultural productivity due to permanent changes in technology or the environment. By focusing on short-run changes in the weather, it is plausible that other factors of production, such as capital or the allocation of land, are held constant, allowing me to identify the effects of labor reallocation on manufacturing outcomes rather than any collective change in factors of production. In support of this premise, I find that increases in temperature have no effect on capital, management, or the entry of new plants.

These results suggest that the reallocation of labor across sectors could play an important role in attenuating the economic consequences of agricultural productivity shocks. Counterfactual estimates, examining the impact of temperature on total GDP, suggest that in the absence of labor reallocation total economic losses would be up to 40% larger. This highlights the role that liberalising goods and labor markets can play, as well as the importance of the local policy environment, in managing the economic consequences of weather-driven changes in agricultural productivity. In addition, I estimate that mitigating the adverse effects of temperature on manufacturing could offset the aggregate effects of temperature by up to 72% in the absence of any adaptation in the agricultural sector, suggesting that there

[2] Understanding whether the differences between casual and manufacturing workers in the manufacturing sector are driven by frictions or human capital differences is beyond the scope and capacity of the data and so remains an important question for future research.

could be considerable gains associated with managing the adverse effects of temperature in non-agricultural sectors. Collectively, these results provide insights into an important mechanism through which economic agents are able to manage climatic influence on economic outcomes, as well as highlighting the sensitivity of non-agricultural sectors to temperature increases.

The remainder of the paper is structured as follows: section 2 examines the relationship between weather and agricultural production; section 3 investigates the degree to which workers are able to move across sectors and space in response to weather-induced labor demand shocks; section 4 explores the impact of labor reallocation on manufacturing outcomes; section 5 discusses the implications of these results, considering the degree to which labor reallocation across sectors could offset losses to agriculture; section 6 concludes.

2 The Effects of Weather on Agricultural Markets

As in many developing countries, agriculture plays an important role in India's economy. During the time period of this study – the beginning of the 21st century –, agriculture accounted for roughly 15–20% of GDP, 60–70% of land use, and 40-50% of employment – many of whom are landless laborers employed on daily contracts.

A key feature of India's agricultural landscape is its dependence on the timing and intensity of the monsoon (Rosenzweig and Binswanger, 1993).[3] Rainfall plays an important and salient role in the production of crops; however, the role of temperature, is a consideration often neglected in economic analysis. The monsoon's arrival in early summer is especially important for the kharif season, which corresponds with this period, but also for the rabi season, which begins at the end of the kharif season and continues through the cooler autumn and winter months before being harvested in the spring. Consequently, rabi yields are highly dependent on the degree to which rainfall can be stored in the soil. High temperatures prior to the monsoon affect the onset of the monsoon – a thermally driven phenomenon –, the degree to which rainfall drains from the soil, and soil temperature, which is important for seed germination and plant growth. High temperatures during the monsoon directly affect the kharif crop and increase the rate of evapotranspiration, which affects the availability of moisture in the soil, necessary for rabi crop production. Finally, high temperatures directly affect the rabi crop, even in the case in which irrigation is used.[4]

[3]During the period of study less than 30% of cultivated land is irrigated.

[4]While temperature is an important determinant of vapour pressure deficit, which irrigation can alleviate, around one third of the effects of temperature on yield losses arise due to an increase in the pace of crop development, which provides less time for the plant to develop and absorb nutrients and calories (Schlenker and Roberts, 2009). Fishman (2012) demonstrates these effects in the context of India by showing that

In this section I examine the effects of weather on two sets of agricultural outcomes. First, I examine the degree to which weather affects agricultural production in India, identifying the sign and magnitude of this relationship. Second, I examine the effects of weather on agricultural prices. This provides an insight into the expected response of labor following a change in agricultural productivity. A priori, it is ambiguous as to whether a reduction in agricultural productivity will result in an increase or decrease in the demand for labor. In a state of autarky, a reduction in agricultural production will result in an increase in prices as supply falls. Jayachandran (2006) shows that if workers have an inelastic labor supply and face a binding subsistence constraint for food (only relevant in the absence of trade), then a reduction in agricultural production will result in an increase in agricultural labor. Furthermore, an increase in prices could reduce the consumption base of the local economy, reducing demand for other commodities (Henderson et al., 2012, Soderbom and Rijkers, 2013, Santangelo, 2015, Emerick, 2016). By contrast, if the local economy is open to trade, then consumption and production are separable. In a state of autarky, agricultural surplus is necessary for the movement of workers into non-agricultural production, as the local economy is responsible for feeding itself. Only when enough food is produced can the economy focus on producing other products. However, when an economy is open to trade, the local economy does not need to produce food itself. Food can be imported and paid for by the export revenues of other commodities. Consequently, instead of rural prosperity fuelling the movement of workers out of agriculture – the historical norm for many developed countries –, rural deprivation pushes workers out of agriculture into other sectors of the economy. In the case of free trade, prices in the local economy are exogenous, set on the global market. Consequently, a local change in production will have a more muted affect on the price of tradable products if the locality is more open to trade, resulting in a change in local comparative advantage. Appendix A presents a simple model based on Matsuyama (1992) demonstrating how the comparative statics vary based on market integration. By understanding the responsiveness of prices to changes in the weather, we can gain an insight into the degree to which Indian districts are integrated into other markets, either national or international, allowing us to postulate the direction in which labor might move following a change in agricultural productivity. Section 3 will then test these insights directly using worker-level data on employment and wages.

higher temperatures still have a direct effect on rice yields – a crop known to be naturally resistant to higher temperatures – after controlling for irrigation.

2.1 Data – Yields and Prices

Data on crop yields and farm-gate prices come from the ICRISAT Village Dynamics in South Asia Macro-Meso Database (henceforth VDSA), which is a compiled from a number of official government data sources. The data analysed cover 12 major crops across 302 districts in 19 states between 1960 and 2009.[5] For comparability with the other datasets I restrict my attention to the period 2001–2007. For each crop and district, the data provide the total area planted, total production in tonnes, and farm-gate prices. It is straightforward to calculate yields as total production divided by total area planted. I also calculate the value of production, defined as price multiplied by yield. Prices, by crop, are deflated to 2001 Rs. Panel A of Table 1 provides summary statistics for the VDSA data.

2.2 Data – Rainfall and Temperature

Rainfall and temperature data are collected from the ERA-Interim Reanalysis archive, which provides 6-hourly atmospheric variables for the period on a $0.25° \times 0.25°$ quadrilateral grid. Daily variables are calculated for each district centroid using inverse distance weighting from all grid points within 100km. The weight attributed to each grid point decreases quadratically with distance.[6] Although India has a large system of weather stations that provide daily readings dating back to the 19th century, the spatial and temporal coverage of ground stations that report temperature and rainfall readings has sharply deteriorated over time. Furthermore, there are many missing values in the publicly available series. If we were to base the construction of this data on a selection rule that requires data for 365 days of the year, the database would have very few observations. Reanalysis data provides a solution to these issues and to endogeneity concerns related to the placement of weather stations, variation in the quality of data collection, and variation in the quantity of data collected. By combining observational data, from ground stations and remote-sensing products (satellites), with global climate models, reanalysis data provides a consistent best estimate of atmospheric parameters over time and space (Auffhammer et al., 2013). This results in an estimate of the climate system that is separated uniformly across a grid, that is more uniform in quality and realism that observations alone, and that is closer to the state of existence than any model could provide alone. This type of dataset is increasingly being used by economists, especially

[5] The 12 crops are Barley, Cotton, Finger Millet, Groundnut, Linseed, Maize, Pearl Millet, Rice, Rape and Mustard Seed, Sorghum, Sugarcane, and Wheat.

[6] The results are robust to alternative methods of construction, including: linear weights; cubic weights; the simple average of each point in the district; the average of each point in the district weighted by the area share of cultivated land; and the average of each point in the district weighted by population. Measures based on averages result in a smaller sample size, as some districts do not contain a data point and require the inverse distance weighting procedure.

in developing countries, where the quality and quantity of weather data is limited.[7] Panel D of Table 1 provides summary statistics for the ERA-Interim Reanalysis Data.[8]

2.3 Empirical Specification – Yields and Prices

The unit of observation in this analysis is the crop × district level.[9] In 2001, the average district population was 1.75 million and the average area was 5,462 km^2 (Census of India, 2001).[10] The main empirical specification for estimating the effect of weather on agricultural outcomes is based on the following model,

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

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

The last term is the stochastic error term, ε_{cdt}. I follow the approach of Hsiang (2010) by assuming that the error term ε_{dt} is heteroskedastic and serially correlated within a district over time (Newey and West, 1987) and spatially correlated across contemporaneous districts (Conley, 1999). For each result I loop over all possible distances up to 2000km, selecting the parameter value that maximises the standard errors. I then repeat this exercise for serial correlation, consistently resulting in a kernel of 1 year.[11]

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

[7] All results are broadly robust to the use of alternative rainfall and temperature datasets from both satellite (TRMM) and ground station (UDEL) sources.

[8] Further details on all data sources are available in appendix B.

[9] Results are robust to aggregating across crops, using 2001 area weights, or to using the main crop in each district, defined using area planted in 2001.

[10] This is roughly twice the average area of a U.S. county (2,585 km^2) and nearly 18 times greater than the average population of a U.S. county (100,000). When compared to commuting zones and labor market areas in the U.S. – developed because county boundaries are not considered adequate confines for an area's local economy and labor market –, Indian districts are approximately 4 times the population size (401,932) and around half the area (11,396 km^2).

[11] Results are also robust when standard errors are clustered at the state level. Fisher et al. (2012) report that clustering at the state level in the U.S. provides equivalent results to directly accounting for spatial correlation using the Conley (1999) standard error adjustment. The average state size in India, when compared to the United States, is roughly similar when compared to states east of the 100th meridian, the historic boundary between (primarily) irrigated and (primarily) rainfed agriculture in the United States.

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

As discussed, temperature is important for agricultural production both during and outside of the monsoon period. Consequently, I use crop calendars to define the relevant time period over which to construct the temperature variables. Alternative specifications, accounting for non-linearities in the temperature schedule are presented in Appendix E. Total rainfall is calculated for each state's monsoon period, beginning with the first month in which total monthly rainfall exceeds 100mm and ending with the first month that rainfall falls below 100mm.

2.4 Results – Yields and Prices

In Table 2 I estimate that a 1°C increase in temperature is associated with a 12.7% reduction in yield (column 1) and a 12.6% reduction in the value of production (column 2). In addition, a 100mm increase in rainfall is associated with a 1.15% increase in yield and a 1.07% increase in the value of production.

It is interesting to note that, in terms of its relative contribution, a one standard deviation change in temperature is shown to have a much larger effect on production (4.39%/SD) when compared to a one standard deviation change in rainfall (2.05%/SD), highlighting the important role that temperature plays in Indian agriculture.[12] This suggests that the importance attributed to rainfall for agricultural production in India may have been overestimated by the omission of temperature in previous work. Alternatively, it may have been the case that over time, farmers have become more effective in managing the effects of rainfall shocks, given the salient nature of the monsoon. This may also be due to the fact that rainfall is storable and can be substituted with ground water resources (manually, or through the use of irrigation systems), whereas the effects of temperature are more difficult to address, requiring heat-resistant crop varieties. The use of irrigation has been shown to offset the adverse effects of rainfall shortages; however, high temperatures still have a direct effect on yields even in the presence of irrigation (Fishman, 2012).

To consider the consequences of agricultural productivity shocks on labor demand, it is also of interest to understand the degree to which weather affects agricultural prices. In column 3 we observe that, on average, neither temperature or rainfall has a significant statistical or economic effect on agricultural prices.[13] This suggests that Indian districts

[12]These results are robust across weather data sets and over an extended period of analysis dating back to the 1960s.

[13]Allen and Atkin (2015) find a similar result looking at the effects of market access on agricultural prices in India between 1960 and 2010.

are reasonably well integrated with other markets, and can be considered as small, open economies. Consequently, a reduction in agricultural production should be associated with a reduction in the demand for agricultural labor, resulting in an outflow of workers into other tradable sectors of the economy due to a change in local comparative advantage. The next section formally tests this hypothesis.

3 The Effects of Weather on Employment, Wages and Migration

Given the significance of weather as a driver of short-run agricultural productivity, it is of interest to understand how these effects feed into labor market outcomes, providing insights into the consequences of weather shocks on the economic lives of agricultural workers. In this section I examine the effects of weather on wages, employment and unemployment within districts. In addition I explore the effects of weather on migration, examining the degree to which weather shocks in other districts affect employment outcomes in destination districts. This exercise provides insights into the relative importance of labor movements across vs. within districts in response to changes in agricultural productivity, as well as helping to bound local labor markets in India.

3.1 Data – Wages and Employment

Data on wages, employment and migration come from the National Sample Survey Organisation (hereafter, the NSS employment survey). The NSS employment survey is a nationally representative household survey which collects information on employment and wages in rural and urban areas. For the purpose of this analysis I make use of NSS survey rounds 60, 61, 62 and 64, covering 2003–04, 2004–05, 2005–06, and 2007–08. The level of analysis using the NSS data is at the district level. I restrict my attention to the sample of districts used in the analysis of agricultural yields, covering both rural and urban areas. I calculate the average day wage and the likelihood of being employed in each sector. The analysis focusses on four sectors, broadly defined as agriculture, manufacturing, services, and construction. The average daily wage is defined as the total wage received divided by the number of days worked over the previous seven days. The likelihood of being employed in each of the aggregated sector in a given district-year is calculated from individual responses to a survey question on their principal sector of engagement or whether they are unemployed, and provides district-level labor force employment share. Panel B of Table 1 provides summary statistics for wages and Panel C provides summary statistics for employ-

ment and unemployment shares. Agriculture accounts for an average of 44% of the labor force, with manufacturing employing 23%, services 18%, and construction 6%. Unemployment is is 8% of the labor force.[14] Examining the differences in wages across sectors, we observe that the wage that agricultural laborers receive on average is significantly lower than the non-agricultural wage. Whether this unconditional wage gap is driven by adjustment costs, human capital differences, compensating differentials associated with sector-specific amenities, or bargaining power, is unclear; however, examining the degree to which workers are able to move across sectors in response to short-run productivity shocks provides some insight into the degree to which adjustment costs may be a first-order concern in this context.

3.2 Data – Migration

An important consideration is the degree to which workers may move across space, rather than sectors. Round 64 of the NSS Employment Survey 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 ($\sum_{S_d \neq S_o} \sum_{\ell_d \neq \ell_o \in S_d} m_{od}$). Consequently, 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 (2015) and use the 2001 Indian Population Census, extracting data on migrant workers by state of last residence. For each destination district, ℓ_d, I observe: the number of migrant workers from the same district (M_{dd}); the number of migrant workers from other districts in the same state ($\sum_{\ell_o \neq \ell_d \in S_d} M_{do}$); the number of migrant workers from districts in other states ($\sum_{S_o \neq S_d} \sum_{\ell_o \neq \ell_d \in S_o} M_{do}$). I combine these data to estimate seasonal migration flows $\hat{m}_{od}$, using the following algorithm:

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

[14] Unfortunately, it is not possible to explore entry and exit from the labor force.

I deviate from Imbert and Papp (2015) 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 characterisation 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 decentralising, from urban to peri-urban and even rural areas, taking advantage of cheaper labor and vastly cheaper land prices (Ghani et al., 2012, 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.

On average, rural-origin migrants comprise the bulk of migration flows, accounting for nearly 90% of all seasonal migration. 66.1% of migrants move within the same district, 2.6% of migrants move to another district within the same state (shared among an average of 15 districts per state, 0.17% per district), and 31.3% move to a different district in a different state (shared among an average of 577 districts, 0.05% per district).[15] However, most strikingly, we observe that there is very little seasonal migration in absolute terms – only 1.1% of the population 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, 2015, Morten, 2013).

These insights have potential implications for the effects of localised 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 localised 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 localised 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 localised temperature shocks in origin districts on employment and wages in destination districts to understand the degree to which localised productivity shocks propagate through labor markets across space.

[15] 593 districts - 1 state, i.e., an average of 16 districts = 577 out-of-state districts on average

3.3 Empirical Specification – Employment, Wages, and Migration

In analysing the effect of weather on employment, wages, and migration, the unit of analysis is the district level. The main empirical specification for estimating the effect of weather on local labor market outcomes is based on the following model,

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

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

As in the analysis on agricultural outcomes, $f(w_{dt})$ is a function of rainfall and temperature. In the most basic specification, $f(w_{dt})$ is modelled as a function of daily average temperature measured over the agricultural year, and total rainfall measured over the state-specific monsoon period. Alternative specifications, accounting for non-linearities in the temperature schedule are presented in Appendix E.

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

The specification examining the degree to which weather-driven changes in agricultural productivity in "foreign" districts affect local labor market outcomes through migration differs slightly.

Using the bilateral migration flows discussed in section I construct a spatial weights matrix summarising the migratory relationship between each district. As mentioned, migration flows between ℓ_o and ℓ_d produce and $o \times d$ 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 district o to district d. In the case that all migration is spread equally between all districts, each 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.

3.4 Results – Wages, Employment, and Migration

Table 3 presents the effects of temperature and rainfall on the average wage of workers in each sector within the local economy. A priori, the effect of weather on the average wage is ambiguous, as the overall effect depends on the change in composition of the workforce in each sector as well as the direct effects of temperature and rainfall changes. If, for a given level of demand, hot, dry weather reduces the supply of labor due to avoidance behavior then the average wage will rise. If, for a given level of supply, hot dry weather reduces the demand for labor there is less work available and so the average wage will fall. We observe that an increase in the daily average temperature is associated with a reduction in the average day wage for agricultural workers (5.16%/ 1°C), consistent with a reduction in the demand for agricultural labor. As discussed, this could well be a function of both supply and demand forces, if workers are less willing to work in the heat, counteracting the reduction in the average wage. However, it is clear that the demand effect dominates. While this acts as an insurance mechanism for farm owners, a reduction in the average wage combined with a reduction in the availability of work – on the intensive or the extensive margin – could have significant welfare effects on agricultural workers if they are limited in their ability to find other work.

Interestingly, we see that rainfall limited effects on the average day wage. The sign on the estimated coefficient is negative and it is marginally significant. Furthermore, this effect is driven by an increase in the denominator (days worked in agriculture) rather than any change in the wage bill received. By contrast, temperature effects are driven by a reduction

in the numerator, the wage bill. As discussed, rainfall is estimated to have less of an effect on agricultural production and so the impact on agriculture may not be significant enough to affect labor market outcomes. Associated with this consideration, it may simply be the case that, due to the relatively short time-series, there is not enough power to identify these effects.

In addition to the effects on agricultural wages, we observe that an increase in temperature is associated with a reduction in the average day wage in manufacturing (3.4%/ 1°C); however this effect is not statistically significant. Again it is not clear as to how the average day wage in manufacturing should respond. In a simple model of labor reallocation, the movement of workers across sectors should reduce the average wage in the destination sectors. However, this depends on how the inflow of workers affects the wages of the incumbent workers. In the context of manufacturing where the tasks of workers is less uniform than in agriculture, there may be complementarities between worker types, which could increase the average wage in manufacturing. However, the limited movement in wages across other sectors, may simply indicate that workers are not moving across sectors. To understand the degree to which workers are moving, I estimate the effects of weather on employment and unemployment as shares of the labor force, identifying the degree to which workers are able to move across sectors, and find jobs, in response to reductions in the demand for agricultural labor.

Table 4 presents the results of this analysis. We observe that an increase in the daily average temperature is associated with a significant reduction in the district share of agricultural employment (11%/ 1°C). Combined with the wage results, this indicates that temperature increases are associated with significant reductions in the demand for agricultural labor. The question remains as to whether these workers are able to find employment in other sectors of the economy, or whether they become unemployed. Consistent with the inferences drawn from the effects of weather on agricultural prices, we observe that the reduction in the share of agricultural employment is offset by an increase in the share of manufacturing employment (7.61%/1°C) (and a smaller increase in the share of services employment (3.86%/1°C)). Of interest, we observe that there are no changes in unemployment, suggesting that workers in India are relatively unconstrained in their ability to move across sectors in response to transitory labor demand shocks.

Consistent with the premise that the effects of rainfall on agricultural production are not sufficient to drive labor market outcomes, rainfall is shown to have no significant effect on changes in the composition of employment in the local economy.[16] This is consistent with the previous results, demonstrating that temperature has a relatively more important effect on agricultural production than rainfall – a premise that has found support in a number

[16]These results are robust across alternative weather data sets.

of other recent studies, emphasising the importance of temperature variation over rainfall as a driver of economic outcomes (Hsiang, 2010, Dell et al., 2012, Gray and Mueller, 2012, Burgess et al., 2014, Mueller et al., 2014, Burke et al., 2015).

In addition to looking at the effects of weather on local economic activity, I also examine the degree to which weather may affect labor market outcomes through migration. The purpose of this exercise is to examine whether short-run changes in the weather result in a reallocation of labor across space, distorting the definition of the local labor market and, consequently, the interpretation of the results, as well as being an outcome of interest in its own right. In particular, it is important to understand the degree to which changes in the population may distort changes in labor force shares. If increases in temperature results in out flows of workers then this would mechanically increase the employment share in the manufacturing and services sector. However, this would also mechanically increase the unemployment rate, even if there were no changes in unemployment.

Table 5 presents the results of this exercise. I find that the migration-weighted weather effects have no effect on employment shares in destination markets, indicating that there is little migration across districts in response to temperature increases. Consequently, local labor markets in India can be bounded at the district level. The reason behind the limited migration remains unclear: on the one hand workers may face significant adjustment costs across space; on the other hand, the ability of other sectors to absorb workers in response to sectoral productivity shocks somewhat mitigates the need to move across space.

Collectively, the results presented in this section suggest that workers in India are relatively able to move across sectors in response to transitory labor demand shocks, suggesting limited constraints on the supply-side. Furthermore, there appear to be limited demand-side constraints in response to these transitory labor demand shocks, with the manufacturing sector absorbing a significant share of these workers.

4 The Effects of Weather on Manufacturing

Having provided evidence to suggest that agricultural workers are relatively able to move across sectors in response to weather-induced changes in agricultural productivity and that the manufacturing sector is a major absorber of these workers, it is of interest to understand what these workers do and how they affect the productivity of firms and the labor market outcomes of incumbent workers. In turn these insights will help to shed light on the degree to which labor reallocation can attenuate the economic consequences of temperature increases.

4.1 Data – Manufacturing Plants

Data on manufacturing come from the Annual Survey of Industries (ASI) collected by the Ministry of Statistics and Program Implementation (MoSPI), Government of India. The ASI covers all registered industrial units that employ 10 or more workers and use electricity, or employ at least 20 workers and do not use electricity. The ASI frame is divided into two schedules: the census schedule, which is surveyed every year, and the sample schedule, which is randomly sampled every few years. The ASI has a much wider coverage than other datasets, such as the Census of Manufacturing Industries (CMI) and the Sample Survey of Manufacturing Industries (SSMI), and is comparable to manufacturing surveys in the United States and other industrialised countries. However, the ASI does not cover informal industry that falls outside the Factories Act of 1948. The formal sector accounts for approximately two-thirds of manufacturing output in India and is therefore not representative of all manufacturing activities. It is, however, representative of tradable manufacturing in India, since the informal sector trades very small volumes, if at all. Consistent with this premise Santangelo (2015) finds that there are no movements of workers into the informal manufacturing sector following rainfall-driven changes in agricultural productivity. Appendix B provides more details on the ASI data preparation. The sample used cover an average of 14,876 firms observed between 2001 and 2007, resulting in a total of 103,273 firm-year observations.

The outcomes of interest are the log of total output, employment, and the average day wage (defined as the total wage bill/the total number of man days worked during the year). Employment outcomes are examined for both permanent (non-managerial) workers and contract workers. The distinction between contract workers and permanent workers is important for this analysis, especially for regulated firms.[17] Contract workers are on casual contracts and so a priori are the type of worker that one would expect to move between the agricultural and manufacturing sector.

Using worker-level data from the NSS (discussed in section 3), 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 6 shows that there is a significant wage gap between permanent manufacturing workers and agricultural workers, with permanent manufacturing workers earning 1.54 times more than agricultural workers, within local labor markets after controlling for individual characteristics.[18] However, we observe that the average wage gap between casual manufacturing workers and agricultural workers

[17]The distinction between contract and permanent workers is less clear for unregulated firms. However, within unregulated firms we observe that contract workers earn less than permanent workers and so may be characterized as less skilled, or in more temporary/casual positions.

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

almost disappears after controlling for individual characteristics, with casual manufacturing workers earning 9% more than agricultural workers. Consequently, there is greater common support between the wages of contract workers and agricultural workers, indicating that within low-skill groups workers 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 characterised as dualistic across types of activities or skill. The fact that non-agricultural sectors contain workers that are more likely to engage in more skilled or productive activities conflates the interpretation of a dualistic labor market across sectors. However, 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.

In addition to the outcome variables described above, I construct two measures of productivity. The first is a simple measure: output per worker. While this is a crude measure of productivity, it provides a relatively useful measure of the average labor productivity of the firm. The second measure is an estimate of total factor productivity. Appendix B provides an explicit model of TFP, in the context of a profit-maximising firm, that I use to construct my empirical estimates.

4.2 The Labor Regulation Environment in India

The combination of manufacturing firm-level data with meteorological data provides the basis of this empirical analysis. However, this is not sufficient to identify how the movement of labor out of agriculture affects economic outcomes in the manufacturing sector. The key empirical challenge relates to the fact that, while exogenous changes in temperature are an important driver of short-run agricultural productivity, there are potentially many empirically relevant channels through which temperature could affect manufacturing outcomes. Consequently, any estimate of the reduced form estimate of temperature on the outcomes of interest will provide the net effect of all empirically relevant channels.

To try to address this challenge, I set out to identify the labor reallocation channel, net of the remaining empirically relevant channels, by exploiting variation in the propensity of firms to absorb workers in response to transitory weather shocks. To do this, I exploit a combination of spatial variation and firm-level exposure to India's labor regulation environment. In more flexible labor market environments, regulated firms should be relatively more able to absorb workers in response to transitory changes in labor demand, compared to firms in rigid labor market environments. Unregulated firms should not be directly affected by the regulation, and so there should be no differential effects of temperature on unregulated

firms across labor regulation environments.[19]

Industrial regulation in India has largely been the result of central planning; however, the area of industrial relations is an exception to this, providing spatial variation in firms' incentives regarding the hiring and firing of workers following transitory changes in labor demand. The key piece of legislation used to measure state-level variation in sectoral mobility is the Industrial Disputes Act of 1947 (hereafter the IDA). The IDA regulates Indian Labor Law concerning trade unions, setting out conciliation, arbitration, and adjudication procedures to be followed in the case of an industrial dispute, and was designed to offer workers in the formal manufacturing sector protection against exploitation by employers. Up until the mid 1990s, the IDA was extensively amended at the state level, resulting in spatial variation in labor market rigidities. Besley and Burgess (2004) use these extensive state-level amendments (113 in total) to construct a measure of the labor regulation, environment studying its impact on manufacturing performance and urban poverty. By examining the amendments made in each state over time, states are coded as either neutral, pro-worker, or pro-employer. A pro-worker amendment is classified as one that decreases a firm's flexibility in the hiring and firing of workers; Pro-employer amendments are classified as increasing a firm's flexibility in hiring and firing. Importantly, one may be concerned that agricultural volatility or weather may have been correlated with the timing or the direction of amendments; however, fortunately I provide evidence to suggest that this isn't the case (see Appendix D).

The cumulation of these scores over time determines the state's labor regulation environment. Consequently, West Bengal, Maharashtra and Orissa are assigned as pro-worker states (rigid). Rajasthan, Tamil Nadu, Karnataka, Kerala and Andhra Pradesh are assigned as pro-employer states (flexible). The remaining states are assigned as neutral. This assignment captures spatial variation in the propensity of firms to take advantage of transitory labor supply changes arising from year-to-year changes in agricultural productivity.

However, state-level variation is not sufficient to identify the labor reallocation channel, as it may simply capture the heterogeneous effects of weather, general equilibrium effects, or other state-level variation, confounding the interpretation of the estimated coefficients.[20] I therefore combine this spatial variation with firm-level exposure to the regulation based on chapter 5b of the IDA, which specifies the size that firms can become before the IDA has a binding effect. The firm-size threshold is 50 in West Bengal, 300 in Uttar Pradesh, and 100 elsewhere.[21] Consistent with these rule I demonstrate that that there is evidence

[19] In theory, unregulated firms may be affected indirectly through spillovers. For example, in rigid labor market environments there may be relatively increase in employment at unregulated firms, due to the limited labor market opportunities in the regulated sector.

[20] Although, importantly there does not appear to be any common differential effect of temperature on non-manufacturing sectors across labor regulation environments (see Appendix D).

[21] Results are robust to applying a uniform threshold across all states away from the regulated threshold,

of bunching in the raw data just below the firm-size employment threshold for rigid labor market environments, but not for flexible labor market environments (see Appendix D).

A further consideration is whether the workers moving out of agriculture are likely to be affected by the IDA. A priori we would expect these workers to enter the regulated formal manufacturing sector as casual contract workers. This raises an important question about the degree to which the labor regulation environment impacts the employment of casual workers. Contract workers are not directly considered as workmen under the IDA and, consequently, are not *de jure* regulated within manufacturing firms. However, this does not mean that contract workers are not affected by the IDA (Bertrand et al., 2015, Chaurey, 2015). Contract workers are still *de jure* regulated by the IDA under the contractor that hires them. Consequently, the availability of these workers to firms in rigid labor market environments may be directly affected by the willingness of contractors to put these workers on the books in response to transitory changes in the weather. In addition, contract workers may be *de facto* affected by the IDA. On the one hand, the exemption of contract workers from the IDA may provide an added incentive to hire contract workers in rigid labor markets, allowing employers to bypass some of the regulations in the IDA. If so, this would imply that the labor reallocation channel would be relatively larger in rigid labor market environments. Looking at the data, one observes, consistent with this argument, that the share of firms using contract workers – an extensive margin measure – is higher in rigid markets than in flexible markets (see Figure 1). On the other hand, the use of contract workers has been vigorously, and in some cases violently, opposed by unions and permanent workers, suggesting that firms may face significant costs associated with hiring contract workers, especially in rigid labor market environments. Furthermore, the Contract Labor Regulation and Abolition Act of 1970 prohibits the use of contract labor if the work "is done ordinarily through regular workmen in that establishment." To the degree that this is enforced, this restricts the degree to which firms can bypass the IDA. Consequently, in rigid labor market environments, where it is expected that firms have to negotiate with unions over decisions that affect the labor force, the hiring of contract workers, in response to transitory changes in labor availability, may be restricted. In support of this premise we observe, on the intensive margin, that the share of workers employed as contract workers is higher in flexible labor market environments, suggesting that, conditional on hiring contract workers, firms in more flexible markets are able to hire more casual workers than firms in rigid labor markets (see Figure 1). Given that, on average, there is no difference in the total number of workers employed by firms across labor regulation environments, this implies that there is a higher proportion of contract workers in flexible than in rigid labor market environments (Table 7).

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mitigating concerns that the results could be driven by the movement of firms around the size threshold.

In practice, whether there is a differential propensity to hire more casual workers in rigid or in flexible labor market environments is an empirical question. Most importantly, it does not affect the identification of the labor reallocation effect, which simply requires that there be a differential effect of temperature across labor regulation environments for regulated firms, but not unregulated firms.

Despite providing evidence of bunching in the firm-size distribution in rigid labor market environments, the fact that weather was not a driver of the amendments made to the IDA, and that the spatial variation in the IDA does not appear to have a differential effect on other unregulated sectors, threats to identification still remain if other factors that are correlated with temperature, the labor regulation environment, and outcome variables differ between regulated firms above the regulatory thresholds, but not unregulated firms below the regulatory threshold. This threat can be tested directly as below the regulatory threshold, there should be no direct differential impact of temperature on firms across labor regulation environments, and any differences that do arise help to sign the bias of the effect on regulated firms. The identification assumption is therefore that there are no other confounding factors across labor regulation environments that differentially affect firms above the regulatory firm-size threshold, but don't differentially affect firms below the regulatory firm-size threshold. An initial examination of this assumption through simple difference-in-means tests suggests that there do not appear to be any obvious differences in the characteristics of firms that would raise concerns (Table 7). The following section presents the empirical specification, allowing for a more formal test of this identification assumption.

4.3 Empirical Specification – Manufacturing Outcomes

To identify the sign and magnitude of the labor reallocation channel, I interact the net effects of weather with a measure of the labor regulation environment, splitting the sample at the regulatory firm-size threshold. The estimation equation for both samples is written as follows,

$$\log Y_{ijdt} = \beta f(w_{dt}) + \gamma f(w_{dt}) \times \textsc{Flexibility} + \alpha_{jd} + \alpha_{jt} + \phi_s t + \varepsilon_{ijdt} \tag{1}$$

The dependent variable, Y_{ijdt}, is the natural log of: total output (sales), employment (by worker type), the average day wage (by worker type), and various produtivity measures. The unit of analysis is firm i, in sector j, in district d, at time t.

District $\times$ industry (α_{jd}) fixed effects absorb all unobserved time-invariant variation within these dimensions; industry $\times$ year (α_{jt}) fixed effects control for sector-specific time-varying differences in the dependent variable that are common across districts; and a set of

flexible state-specific time trends ($\phi_s t$) relaxes the assumption that shocks or time-varying factors that affect the outcome variables are common across districts.

As in the previous sections, $f(w_{dt})$ is a function of rainfall and temperature,

$$f(w_{dt}) = \beta_1(Temperature_{dt}) + \beta_2(Rainfall_{dt}) \tag{2}$$

where total rainfall is measured over the state-specific monsoon period and the daily average temperature is measured over the agricultural year. As for the previous sections, alternative specifications, accounting for non-linearities in the temperature schedule are presented in Appendix E.

The challenge associated with identifying the labor reallocation effect when estimating the simple linear regression model, absent the interaction term, is that β captures the sum of all empirically relevant channels through which temperature affects the manufacturing outcomes. This identifies the effects of temperature, but does not provide an economic interpretation.

The interaction term, $f(w_{dt}) \times$ Flexibility, captures the differential propensity of firms to absorb workers in response to increases in temperature. Flexibility is defined to allow for a continuous measure of the labor regulation environment, based on Besley and Burgess (2004), bounded between 0 and 1. West Bengal is the baseline state, coded 0 as it is the most rigid labor regulation environment. Andhra Pradesh and Tamil Nadu are coded as 1, as they are the most flexible labor regulation environments.

For regulated firms $\gamma_{regulated}$, identifies the labor reallocation effect, net of the remaining empirically relevant channels through which temperature effects manufacturing, β, if $\gamma_{unregulated} = 0$. Any deviations from this condition provide the sign and magnitude of the bias captured in $\gamma_{regulated}$ if $\gamma_{unregulated}$ is not zero. For example a positive differential effect on unregulated firms would suggest that the estimated differential effect on regulated firms would be upward biased. By contrast, a negative differential effect for unregulated firms would suggest that the estimated differential effect on regulated firms would be downward biased.

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

4.4 Results – Manufacturing

Unregulated Firms

I begin by examining the effects of temperature on unregulated firms. Below the regulatory threshold, there should be no direct differential impact of temperature on firms across labor regulation environments.[22] As a result, these estimates do not disentangle the labor reallocation effect, but rather test an important identification assumption: that any additional channels through which weather could affect manufacturing outcomes are constant across labor regulation environments. This also tests for the presence of any additional spatial differences such as general equilibrium effects or other policy differences that are correlated with the spatial dimension of the labor regulation environment.

Tables 8 and 9 present results that provide direct evidence in support of the identification assumption. Consistent with the results in section 3, I find evidence that an increase in temperature is associated with a net expansion of economic activity in unregulated firms (Panel A); however, there is limited evidence of a differential effect of temperature across labor regulation environments on unregulated firms.

The one exception to this is a differential effect in total employment. However, given the absence of other differential effects, it is plausible that this arises due to a spillover in the labor regulation environment itself, rather than differences in the other empirically relevant channels through which temperature affects manufacturing, or other policy or geographic differences. We observe that in more flexible markets there is relatively less hiring in response to temperature increases. This is consistent with the premise that the labor regulation environment may have indirect effects on unregulated firms. If workers are not able to find employment in the regulated sector of rigid labor market environments, we may expect a relative expansion (accounting for the size threshold) of the unregulated sector.

While it is not clear why firms require or distinguish between casual and permanent works in the unregulated market, it is interesting to note that the differential employment effects appear to be driven by contract workers, the type of workers that we might expect a priori to move in response to transitory changes in the demand for agricultural labor. For example, while regulatory constraints are not binding for unregulated firms it is plausible that firms may still have a preference to hire workers into temporary contract positions over permanent positions for other reasons, such as differential administrative costs.

These results suggest two things: 1) that our estimates of the differential effect of temperature are not likely to be biased due to confounding geographic or policy considerations that may be correlated with the labor regulation environment; 2) that any other empirically

[22] As discussed there may be indirect effects of the regulation on unregulated firms.

relevant channels through which temperature may affect manufacturing are constant across labor regulation environments. However, estimates of the differential effect of temperature on contract workers in regulated firms are likely to be a lower bound due to the potential spillover effects of the labor regulation environment onto unregulated firms.

Regulated Firms

In light of the evidence above, suggesting that the other empirically relevant effects of temperature are constant across labor regulation environments, and that other policy and geographic considerations do not appear to be confounding the interpretation of the labor regulation measure I proceed to explore the effects of temperature on regulated firms. Tables 10 and 11 present the results of this exercise.

First, I find evidence that there are limited net effects of temperature on manufacturing output and employment in regulated firms, as well as net reductions in productivity (Panel A). These results are consistent with, though not limited to, an expanding literature which suggests that high temperatures may have an adverse effect on labor productivity (Mackworth, 1946, 1947, Hsiang, 2010, Graff Zivin and Neidell, 2014, Adhvaryu et al., 2015, Graff Zivin et al., 2015, Somonathan et al., 2015). However, it is not clear whether the absence of employment and production effects are true zeros, or whether the labor reallocation effect observed on net in unregulated firms is confounded by other competing temperature effects.

In support of the latter interpretation I find differential effects of temperature across labor regulation environments. In rigid labor market environments I find that increases in temperature are associated with contractions in output, employment and productivity. By contrast, in flexible labor regulation environments we observe relative expansions in output and employment. This is consistent with the premise that firms in more flexible labor market environments have a greater capacity to absorb workers in response to weather-driven changes in agricultural productivity. In addition, we observe that firms are hiring contract workers, with no net or differential change in the number of permanent workers, consistent with anecdotal evidence and a priori reasoning. Related to the discussion of the *de facto* impact of the labor regulation environment on contract workers, the relative increase in the employment of contract workers in more flexible labor markets, suggests that firms in more rigid labor markets may be incentivised against hiring contract workers, at least in response to short-run changes in the availability of workers.

From the workers' perspective, it is reasonable to suppose that agricultural workers on casual contracts would be more likely to find casual work in the manufacturing sector before

moving into permanent work. In addition, the presence of centralized contractors that provide firms with casual labor significantly reduces search costs for these positions compared to permanent positions. This is consistent with the evidence provided by Bryan et al. (2014) in Bangladesh, Franklin (2015) in Ethiopia, and Hardy and McCasland (2015) in Ghana, who demonstrate that, in contexts without contractors, there are significant search costs associated with finding employment.

From the firms' perspective, the results are consistent with the premise that manufacturing firms hire workers on casual contracts as a screening process, rather than hiring movers into permanent contracts straight away. Employers face an adverse selection problem, as they can only discern a worker's true ability after a hiring decision has been made, especially in the absence of employment histories. By using contract workers, firms can learn more about a worker's productivity before deciding whether to hire them permanently. This is consistent with the evidence provided by Heath (2015) who finds that firms in Bangladeshi garment factories hire workers through referrals to mitigate adverse selection and moral hazard concerns. In doing so, firms can punish the referral provider if the new entrant is unproductive. Hardy and McCasland (2015) also highlight the importance of worker screening in the hiring decisions of firms in Ghana.

While there appears to be little impediment to moving across sectors within casual tasks, the absence of employment into permanent manufacturing positions suggests that casual and permanent labor markets are segmented, at least in the short run. Local labor markets in developing countries can therefore be characterised as dualistic, not in terms of sectors (agriculture vs. non-agriculture), but rather in terms of the type of employment in which workers engage (casual vs. permanent). This raises an interesting question about the degree to which casual workers face adjustment costs in the movement into permanent positions. As noted, there is a significant wage gap between casual manufacturing workers and permanent workers. However, while this gap exists, it is less clear how it should be interpreted. On the one hand, wage gaps may represent significant adjustment costs, implying that there are arbitrage opportunities to increase productivity if these costs could be reduced – a misallocation of talent (Banerjee and Duflo, 2007, Restuccia and Rogerson, 2008, Hsieh and Klenow, 2009, Moretti, 2011, Bryan et al., 2014, Gollin et al., 2014, Hsieh et al., 2014, Bandiera et al., 2015a, Bryan and Morten, 2015, Munshi and Rosenzweig, 2015). On the other hand, average wage gaps may simply represent differences in human capital between casual and permanent workers, with low-skilled workers selecting into casual tasks and high-skilled workers selecting into permanent tasks (Roy, 1951, Heckman and Sedlacek, 1985, Heckman and Honore, 1990, Miguel and Hamory, 2009, Beegle et al., 2011, Lagakos and Waugh, 2013, Young, 2013, 2015). This interpretation would suggest that, while average

wage gaps across sectors exist, marginal productivities may be equalised across activities – an efficient allocation of talent. Both of these channels may be further confounded by differences in the bargaining power or amenities across tasks. As discussed, the evidence presented so far, alongside evidence from worker-level mincerian wage regressions, suggests that adjustment costs, to the degree that they exist, are limited across sectors within casual activities.[23]

In addition to the relative expansion of employment and production in flexible labor regulation environments, I also observe that temperature increases are associated with differential wage and productivity effects. Consistent with the relative inflow of contract workers in flexible labor regulation environments we observe a relative fall in the average wages of casual workers in response to temperature increases. Furthermore, we observe that temperature increases are associated with relative increases in the average wage of permanent workers. Given that contract and permanent labor markets are segmented, i.e., we observe no increase in the number of permanent workers, this suggests that the tasks that the casual entrants and permanent workers engage in are complementary in production. Consistent with this premise, we also observe relative increases in average labor productivity and measured TFPR, as well as the number of products produced.[24]

A speculative interpretation of these findings is that the inflow of relatively low-skilled casual workers, freeing up permanent workers to engage in more productive tasks, moving firms down the average cost curve.

However, one concern may be that these effects are driven by accompanying changes in other factors of production, confounding this interpretation of the results. Yet, one of the attractive features of the empirical context and identification strategy is that the movement of workers across sectors is driven by short-run changes in the weather and so one may consider that other factors of production and the technology of the firm are held fixed. Table 12 directly tests this consideration. I begin by looking at the effects of temperature on capital and capital depreciation. If capital were to increase alongside labor, then it would be difficult to attribute increases in productivity and permanent worker wages to the reallocation of labor alone. Consistent with the premise that the other factors of production are held

[23]Unfortunately, it is beyond the scope and capacity of the data to provide inferences about the relative contribution of these channels to the wage gap between casual and permanent manufacturing workers. However, in appendix F I provide an upper bound on the gains from reallocation, under the assumption that the total wage gap between casual and permanent workers is driven by adjustment costs. Understanding the relative importance of the role that adjustment costs play in impeding the movement of workers out of casual employment and into permanent positions remains an important area for future research.

[24]TFPR (CES) allows for imperfect substitution between contract and permanent workers using exogenous estimates of the elasticity of substitution between contract and permanent workers combined with a nested CES production function (see Appendix C for details on estimation).

fixed, we observe that there is no change in capital or capital depreciation in response to temperature changes, and that this effect does not vary across labor regulation environments. Second, I consider the effects of temperature on the number of managers and the wages of managers. While a crude measure of the organisational structure of the firm, this provides some insights as to whether productivity increases could have been driven by organisational change or whether the increase in permanent worker wages could be driven by the extraction of rents from the firm. If this were the case then we may also expect managers to share in these rents. We observe neither an increase in the number of managers nor changes in the average wage of managers, suggesting that neither changes in management nor rent extraction appear to provide first-order explanations for the results. Finally, I explore whether the firm expands the number of plants – a proxy for entry and exit considerations that are not directly observable in the data. Again, we observe that the firm does not open or close plants in response to changes in temperature, suggesting that there are unlikely to be significant changes in the number of firms or in the market structure in response to changes in temperature. These findings suggest that the productivity and wage results can be interpreted as being driven by the increase in casual workers, rather than changes in other factors of production or changes in the technology or management structure of the firm.

In addition to the supporting evidence presented here, a number of additional robustness tests, including the removal of firms around the threshold, specification extensions that account for non-linearities in the temperature distribution, alternative definitions of the labor regulation environment and instrumental variable results, are presented in Appendices D and E.

The above results highlight the problems associated with the identification and interpretation of reduced-form weather results, but demonstrate the insights that can be gleaned from attempting to isolate specific channels and mechanisms through which weather can affect economic outcomes. I show that increases in temperature are associated with contractions of economic activity in rigid labor market environments, where firms are less able to absorb workers in response to weather-driven changes in agricultural productivity. However, in more flexible labor regulation environments I estimate that increase in temperature are associated with a relative expansion of manufacturing production and the employment of casual workers. However, unlike the effects of temperature on unregulated firms, this reallocation does not result in a net increase in output for regulated firms, as the adverse effects of temperature counteract the labor reallocation effect. While it is beyond the scope of this paper, and indeed the capacity of the data, to identify the precise mechanisms through which this residual net effect has an effect on manufacturing outcomes, one thing is clear: if these effects can be mitigated, the realised impact of temperature on manufacturing output through

labor reallocation will be significantly larger, offsetting the economic losses associated with temperature increases in agriculture. The following section explores various counterfactuals, relating to the aggregate consequences of these mechansism.

5 Counterfactual Analysis

In this section I explore what my results imply for aggregate production in India. I consider two sets of counterfactual experiments. First, I consider the counterfactual impact associated with shutting down labor reallocation by increasing the rigidity of the labor market environment across India to the level of West Bengal (the most Pro-Worker State). Second, I consider the counterfactual gains associated with shutting down the adverse effects of temperature on manufacturing.

Baseline Effects

I begin by estimating the baseline effects of temperature on GDP, using data on sectoral GDP for each district, focusing on agriculture, manufacturing, construction and services. Table 13 presents the results of this exercise, showing that a 1°C increase in temperature is associated with a reduction in agricultural GDP (-11.6%/1°C), a reduction in total manufacturing GDP (-2.57%/1°C), and no change in services or construction GDP. Overall, a 1°C increase in temperature is associated with a 2.63% reduction in total GDP.[25]

To explore various counterfactual environments I split total manufacturing GDP into three components: the informal manufacturing sector (34% of GDP), the regulated formal manufacturing sector (22% of GDP) and the unregulated formal manufacturing sector (44% of GDP). Taking as given the estimated effects of temperature on manufacturing output for the regulated and unregulated formal manufacturing sector (presented in Panel A of tables 8 and 10), the residual effect of temperature on the informal sector, necessary to induce a 2.57% reduction in total manufacturing GDP, is -18.3%. These baseline figures are reported in column 1 of Table 14.

Increasing the Rigidity of the Labor Market Environment

In columns 2, and 3 of Table 14 I consider the impact of increasing the rigidity of all labor market environments in India to the levels of West Bengal (the most Pro-Worker State). First, I consider the effects of increasing rigidity only in the regulated formal sector. I do this by inducing a 15.3% reduction in output for firms in the most flexible labor markets

[25] The predicted effect on total GDP from aggregating the estimated effects of a 1 degree increase in temperature on other sectors, i.e., $\sum_s \beta_s \times GDP_s/GDP$ is -3.03%.

(Andhra Pradesh and Tamil Nadu), the effect decreasing in the rigidity of the labor market environment. As such, there is no change in output for West Bengal. In this counterfactual environment a 1°C increase in temperature would be associated with a 4.58% reduction in manufacturing GDP and a 3.31% reduction in total GDP, corresponding to a 9.24% increase in losses to total GDP. Secondly, I consider the effects of increasing the rigidity of the labor market environment in the unregulated formal sector, equivalent to increasing the scope of labor regulation to unregulated firms. In this counterfactual environment losses are even greater. A 1°C increase in temperature is associated with a 11.32% reduction in manufacturing GDP and a 4.25% reduction in total GDP, corresponding to a 40.26% increase in losses to total GDP. These simple counterfactuals highlight the importance of labor mobility, as well as the importance of the local policy environment, in managing the economic consequences of temperature increases.

Shutting Down the Adverse Effects of Temperature on Manufacturing Firms

Next, I consider how much of the losses to GDP could be offset by mitigating the adverse effects of temperature on manufacturing. For example, one could imagine that these effects could be attenuated through the use of cooling technologies.[26] Due to the competing effects of temperature on manufacturing, the net effect on regulated manufacturing firms is zero, and so labor reallocation only offsets the losses associated with the adverse effects of temperature for these firms. By setting the adverse effects of temperature to zero the labor reallocation effect will be positive, offsetting losses to agricultural GDP.[27]

In column 4 I restrict my attention to regulated formal manufacturing firms. In this case, a 1°C increase in temperature is associated with a 1.01% increase in manufacturing GDP and a 2.53% reduction in total GDP. This corresponds to a 16.5% reduction in losses to total GDP.

In column 5, I allow the estimated effects to be extrapolated to the rest of the formal manufacturing sector, expanding "cooling technologies" to unregulated formal manufacturing firms. In this counterfactual a 1°C increase in temperature is associated with a 7.74% increase in manufacturing GDP, and a 1.59% reduction in total GDP. This corresponds to a 47.52% reduction in losses to total GDP.

Finally, in column 6, I allow the estimated effects to be further extrapolated to the

[26] These counterfactual exercises do not address the costs associated with the implementation of such technologies.

[27] One concern relating to the validity of this exercise is that firms may only be hiring workers in response to the reductions in productivity associated with the adverse effects of temperature. Consequently, in the absence of adverse temperature effects, firms may have limited capacity to expand production in the short run. However, the net increase in output and employment for unregulated firms suggest that expansions in response to year-to-year variations in temperature are possible.

informal sector. I estimate that a 1°C increase in temperature is associated with a 12.95% increase in manufacturing GDP and a 0.86% reduction in total GDP. This corresponds to a 71.67% offset in losses to total GDP.

These results suggest that there could be significant gains from mitigating the adverse effects of temperature on manufacturing, and that the movement of workers across sectors could significantly offset the aggregate effects of temperature on local economic activity.

6 Conclusion

One of the salient features of economic life in developing countries is the centrality of agriculture to employment. Consequently, given the inextricable link between agricultural production and the environment, understanding the relationship between economic and natural systems can provide important insights into the economics lives of the poor. While we have a reasonably good understanding about how weather affects agricultural markets, understanding how workers respond to changes in labor demand helps to provide insights into the mechanisms through which climatic influence affects economic outcomes, as well as the functioning of labor markets in developing countries.

Consistent with a large literature examining the effects of weather on agricultural production, I estimate that temperature is a strong driver of short-run agricultural productivity. However, I also estimate that there are no effects on agricultural prices, consistent with a "law of one price", indicating that Indian districts are reasonably well integrated with other markets. A priori, this suggests that reductions in agricultural productivity should result in an outflow of workers into other sectors due to a local change in comparative advantage.

Consistent with this premise, I present evidence to suggest that agricultural workers in India are relatively able to move across sectors within local labor markets when temperature increases, moving chiefly into the manufacturing sector. This movement completely offsets the reduction in agricultural employment, with no increases in unemployment, or population through migration, indicating that the ability of other sectors to absorb workers is a key channel through which workers can manage reductions in the demand for their labor in agriculture. These results highlight the role that market integration and diversification can play in attenuating the aggregate consequences of sectoral productivity shocks.

In light of these results, I explore how this reallocation of labor across sectors affects economic outcomes in the formal manufacturing sector, which is representative of tradable industry in India. The principal challenge associated with identifying the effects of labor reallocation is that there are many channels through which temperature could affect manufacturing outcomes. Consequently, the estimated effect of temperature on manufacturing

outcomes provides a net effect of all the empirically relevant channels, without a clear economic interpretation.

To discern the impact of labor reallocation on these firms, I interact the net effects of temperature with a combination of spatial and firm-level exposure to India's labor regulation environment, providing variation in the propensity of firms to absorb labor in response to short-run changes in labor availability.

For unregulated firms I estimate that the net effect of temperature on production and employment is positive and significant consistent with the premise that workers are able to move across sectors in response to weather-driven changes in agricultural productivity. However, importantly for identification, I estimate that there are no differences in the effects of temperature across labor regulation environments, indicating that any additional channels, through which temperature affects manufacturing, are constant across labor regulation environments. By contrast, for regulated firms I estimate a differential effect across labor regulation markets. In rigid labor market environments, an increase in temperature is associated with a contraction in economic activity, consistent with a literature that suggests that temperature is an important determinant of labor productivity. However, I demonstrate that there is a relative expansion of output and the employment of low-skilled casual workers in flexible labor regulation environments, consistent with the premise that regulated firms in these environments have a greater propensity to absorb workers in response to weather-driven changes in agricultural productivity. These results support the premise that the ability of firms to absorb workers is a key channel through which workers are able to manage agricultural productivity shocks, indicating that the local policy environment can play an important role by affecting the ability of firms to absorb labor.

Furthermore, I estimate that this inflow of casual workers is associated with an increase in the wages of permanent workers as well as increases in productivity, suggesting that there may be complementarities between the tasks that casual and permanent workers engage in. In support of this interpretation, I find that there are no changes in capital, management, or the number of plants, suggesting that the effects are driven by labor reallocation, rather than changes in other factors of production, or the technology or organization of the firm.

In considering the aggregate consequences of these effects, I explore two sets of counterfactual exercises using data on district level, sectoral GDP. First, I estimate that in the absence of labor reallocation total economic losses would be up to 40% larger, highlighting the importance of labor mobility in attenuating the economic consequences of sectoral productivity shocks. Second, I estimate that attenuating the adverse effects of temperature on manufacturing could offset the aggregate effects of temperature by up to 72%, despite the adverse effects that temperature increases have on the agricultural sector. This suggests that

there could be considerable gains to managing the economic consequences of temperature in non-agricultural sectors.

The findings of this paper have three main implications. First, regarding the labor market decisions of the poor, my results suggest that workers in agriculture are highly responsive to changes in the agricultural wage and employment opportunities, resulting in movements across sectors within casual employment activities. These findings suggest that low-skilled workers are relatively substitutable across sectors. However the absence of movement into permanent manufacturing positions suggests that labor markets can still be characterised as dualistic (Lewis, 1954). However, labor markets do not appear to be dualistic across sectors (agriculture vs. non-agriculture) but rather in terms of the type of employment activities in which workers engage (casual vs. permanent). Consequently, when engaged in casual employment, the delineation of activities by sector may have little relevance, with workers engaging in activities across sectors in rural or urban areas of the local labor market. However, as workers move up the skill ladder into permanent jobs, the delineation of employment by sector may start to become more important. Many important research opportunities remain to help improve our understanding of whether workers face constraints that impede their movement out of casual and into permanent employment, and whether these constraints are amenable to policy.

Second, regarding the behaviour of firms, my results suggest that firms in India have the potential to act as a major absorbers of labor, even in the short-run, highlighting the importance of diversification in the management of idiosyncratic productivity shocks. In addition, I demonstrate that even sectors considered to be considerably less climate-sensitive than agriculture can be significantly affected by temperature increases, suggesting that we may significantly underestimate the damages associated with future climate change if we fail to account for non-agricultural impacts. Furthermore, in the face of competing mechanisms we will underestimate the economic importance of these damages. Understanding the relationship between environmental conditions and firm behaviour remains a fruitful area of research; especially questions relating to how the management and innovation of firms may help to manage short- and long-run environmental change.

Finally, regarding climatic influence on economic outcomes, my results show that workers are relatively able to adapt to temperature increases by moving across sectors, and that the ability of firms to absorb these movements is a key channel through which workers are able to manage the effects of weather-driven changes in agricultural productivity. Consequently, we may overestimate the damages associated with future climate change if we do not take into account the adaptation responses of economic agents. Much more work is required to understand how different institutions, systems, technologies, and policies may moderate

the short-run and long-run environmental change so that we are better able to understand the constraints that economic agents face in managing such change. In turn we can better design and implement policy, where necessary, to mitigate the economic consequences of environmental change, today and in the future.

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Figures and Tables

Table 1: Descriptive Statistics - Agriculture and Labor Markets in India (2001–2007)

	Mean	Std. Dev. (within)	Std. Dev. (between)
Panel A: Agricultural Data			
Yield	1.789	0.472	1.683
Value (Rs.)	19,300.67	10,392.71	22,245.56
Production ('000 Tonnes)	113.042	49.626	252.894
Area ('000 Hectares)	59.261	15.051	100.687
Price (Rs./Tonne)	11,995.1	4,012.233	7,431.825
Number of Crops	7.047	0	3,532
Average Crop Share	0.154	0.0276	0.216
Average Share of Main Crop	0.559	0.042	0.176
Panel B: Wage Data			
Average Day Wage: Agriculture	56.482	15.822	21.988
Average Day Wage: Manufacturing	96.720	42.627	37.397
Average Day Wage: Services	186.403	45.826	37.786
Average Day Wage: Construction	81.458	33.010	29.123
Panel C: Employment Data			
District Employment Share: Agriculture	0.445	0.095	0.147
District Employment Share: Manufacturing	0.225	0.062	0.086
District Employment Share: Services	0.183	0.046	0.057
District Employment Share: Construction	0.066	0.031	0.032
Unemployment Share of Labor Force	0.078	0.032	0.043
Panel D: Meteorological Data			
Daily Average Temperature (°C)	24.847	0.271	4.185
Degree Days ($t_L = 17, t_H = \infty$)	3,103.204	90.757	809.660
Degree Days ($t_L = 0, t_H = 17$)	5,995.568	22.590	704.792
Monsoon Rainfall (mm)	927.297	206.509	482.657

Table 2: The Effects of Weather on Agricultural Outcomes

	log Agricultural Outcomes		
	Yield (All Crops)	Value (All Crops)	Price (All Crops)
Daily Average Temperature (°C)	-0.127***	-0.126***	0.000957
	(0.0358)	(0.0323)	(0.0107)
Monsoon Rainfall (100mm)	0.0115***	0.0107***	-0.000795
	(0.00375)	(0.00347)	(0.00181)
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	9,813	9,813	9,813

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table 3: The Effects of Weather on Average Wages

	log Average Day Wages			
	Agriculture	Manufacturing	Services	Construction
Daily Average Temperature (°C)	-0.0516**	-0.0344	-0.0107	-0.0150
	(0.0240)	(0.0558)	(0.0630)	(0.0452)
Monsoon Rainfall (100mm)	-0.00611*	-0.0136	-0.00344	-0.00171
	(0.00365)	(0.00873)	(0.00727)	(0.00700)
Fixed Effects	District, Year, State-Year Time Trends			
Observations	1,067	1,068	1,099	1,035

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled 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 4: The Effects of Weather on the District Labor Force Share of Employment - By Sector

	District Labor Force Shares				
	Agriculture	Manufacturing	Services	Construction	Unemployment
Daily Average Temperature (°C)	-0.110***	0.0761***	0.0386***	0.00115	-0.00596
	(0.0190)	(0.0104)	(0.00758)	(0.00711)	(0.00460)
Monsoon Rainfall (100 mm)	-0.00298	0.00297*	0.00102	-0.00185	0.000836
	(0.00309)	(0.00161)	(0.000976)	(0.00123)	(0.000742)
Fixed Effects	District, Year, State-Year Time Trends				
Average Share	0.445	0.225	0.183	0.066	0.078
Observations	1,105	1,105	1,105	1,105	1,105

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table 5: The Effects of Weather in Foreign Districts on the Share of Employment in Destination Districts - By Sector

	Destination District Labor Force Shares				
	Agriculture	Manufacturing	Construction	Services	Unemployment
Local Daily Average Temperature (°C)	-0.100***	0.0781***	0.0364***	-0.00132	-0.0127**
	(0.0170)	(0.0113)	(0.00763)	(0.00701)	(0.00569)
Local Monsoon Rainfall (100 mm)	-0.00333	0.00304	0.00161	-0.00181	0.000479
	(0.00327)	(0.00185)	(0.000980)	(0.00125)	(0.000838)
Foreign Daily Average Temperature (°C)	-0.0800	-0.0166	0.0195	0.0209	0.0562**
	(0.0534)	(0.0272)	(0.0329)	(0.0182)	(0.0221)
Foreign Monsoon Rainfall (100 mm)	0.00172	-0.000899	-0.00491	-0.00000550	0.00410
	(0.00702)	(0.00408)	(0.00352)	(0.00245)	(0.00308)
Fixed Effects	District, Year, State-Year Time Trends				
Average Share	0.445	0.225	0.183	0.066	0.078
Observations	1,105	1,105	1,105	1,105	1,105

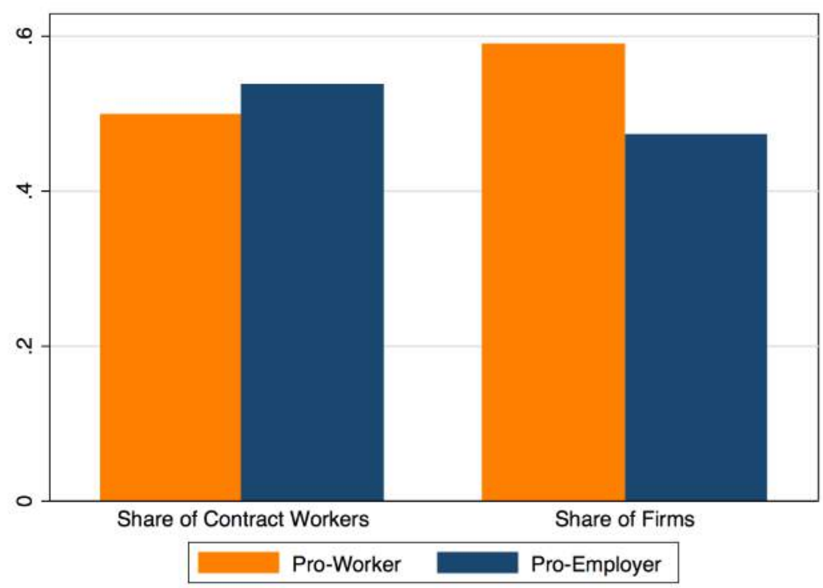
Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table 6: Average Wage Gap (Agriculture vs. Manufacturing)

	India Wide	Within District	Within District Skill Adjusted
Average Wage Gap (Casual Manufacturing Workers)	1.335	1.139	1.094
Average Wage Gap (permanent Manufacturing Workers)	2.210	1.936	1.540
Average Day Wage in Agriculture (Rs.)	52.27	52.27	52.27
Year Fixed Effects	Yes	Yes	Yes
District Fixed Effects	No	Yes	Yes
Individual Controls	No	No	Yes
Observations	50,832	50,832	50,818

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Individual level controls include age, education, and gender. 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 labor, or permanent manufacturing employment. The wage gap is calculated as exp(β). Individual controls include level of education, age, and gender.

Figure 1: Contract Workers Shares – by Labor Regulation Environment



Notes: Share of Contract Workers is defined as the share of contract workers in the labor force conditional on hiring one contract worker, i.e., conditional on hiring contract workers, we observe that Pro-Employer States hire more. Share of Firms is defined as the share of firms that hire any contract workers, i.e., Firms in Pro-Worker States are more likely to hire at least one contract worker compared to Pro-Employer States.

Table 7: Descriptive Statistics - Manufacturing Firms in India (2001–2007)

	Regulated Firms			Unegulated Firms		
	Rigid States	Flexible States	Difference	Rigid States	Flexible States	Difference
Total Output	2,130.215	1,572.613	-557.602	132.982	89.374	-43.607
(Million Rs.)	(609.347)	(508.357)	(869.733)	(37.141)	(16.622)	(46.319)
Total Employment	415.447	477.500	62.053	34.702	39.957	5.255
(Non-mangers)	(94.964)	(113.593)	(198.128)	(7.047)	(4.833)	(7.563)
Employment	54.354	191.157	136.802	12.361	9.977	-2.384
(Contract Workers)	(11.793)	(74.758)	(75.682)	(4.320)	(2.785)	(5.716)
Average Day Wage	156.273	140.061	-16.211	145.138	112.971	-32.167
(Contract Workers)	(11.194)	(7.689)	(17.130)	(29.158)	(8.846)	(36.825)
Employment	361.076	286.332	-74.744	22.340	29.980	7.640
(Regular Workers)	(54.977)	(25.177)	(70.039)	(4.170)	(3.719)	(5.655)
Average Day Wage	302.003	200.478	-101.525	195.141	129.019	-66.121
(Regular Workers)	(71.131)	(23.244)	(87.473)	(47.432)	(12.269)	(58.600)
Employment	53.119	42.526	-10.593	6.827	4.605	-2.221
(Managers)	(11.282)	(7.135)	(16.136)	(2.086)	(0.677)	(2.547)
Average Day Wage	871.471	658.062	-213.409	646.620	371.388	-275.232
(Managers)	(173.962)	(65.288)	(219.641)	(137.602)	(41.575)	(171.595)
Capital	1,483.548	1,229.230	-254.318	80.357	50.814	-29.543
(Million Rs.)	(453.552)	(407.124)	(640.261)	(27.135)	(15.276)	(32.173)
Items Produced	2.997	2.582	-0.414	2.482	2.067	-0.414
	(0.558)	(0.206)	(0.700)	(0.336)	(0.170)	(0.473)
Access to Electricity	0.991	0.987	-0.004	0.973	0.965	-0.007
(%)	(0.005)	(0.004)	(0.007)	(0.023)	(0.014)	(0.032)
Generates Own	0.441	0.643	0.201***	0.142	0.398	0.255**
Electricity (%)	(0.042)	(0.043)	(0.060)	(0.091)	(0.057)	(0.106)
Output per Worker	3.739	2.358	-1.381	3.047	1.869	-1.178
(Million Rs.)	(0.941)	(0.523)	(1.289)	(0.560)	(0.230)	(0.718)
TFPR	6.119	6.082	-0.037	5.468	5.423	-0.045
(Log)	(0.058)	(0.066)	(0.110)	(0.029)	(0.061)	(0.083)

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Rigid States = 0, Flexible States = 1. The sample is restricted to regulated firms. Standard errors are clustered at the State Level.

Table 8: The Effects of Temperature on Manufacturing Firms – Unregulated Firms

	log Output and Employment				
	Total Output	Items Produced	Employment (All)	Employment (Contract)	Employment (Permanent)
Panel A: Net Effect					
Daily Average Temperature (°C)	0.0888** (0.0346)	-0.00753 (0.0106)	0.0324** (0.0149)	-0.0445 (0.0304)	0.0326* (0.0171)
Panel B: Differential Effect					
Daily Average Temperature (°C)	0.119* (0.0708)	-0.0282 (0.0271)	0.147*** (0.0289)	0.0830 (0.0887)	0.0959** (0.0407)
Temperature × Flexible	-0.0470 (0.0992)	0.0321 (0.0384)	-0.177*** (0.0436)	-0.201 (0.136)	-0.0985 (0.0608)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends				
Observations	65,934	65,934	65,921	21,751	60,302

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Panel A presents the results from regression the outcome variable on the level of temperature and monsoon rainfall. Panel B presents the differential effects of temperature across labor regulation environments. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table 9: The Effects of Temperature on Manufacturing Firms – Unregulated Firms

	log Wages and Productivity				
	Avg. Day Wage (All)	Avg. Day Wage (Contract)	Avg. Day Wage (Permanent)	Output per Worker	TFPR
Panel A: Net Effect					
Daily Average Temperature (°C)	0.0110 (0.00898)	0.00440 (0.0129)	0.0181* (0.0108)	0.0449 (0.0300)	0.0149 (0.0156)
Panel B: Differential Effect					
Daily Average Temperature (°C)	-0.0236 (0.0275)	-0.0171 (0.0329)	-0.00817 (0.0306)	-0.0372 (0.0684)	0.0255 (0.0388)
Temperature × Flexible	0.0536 (0.0388)	0.0340 (0.0517)	0.0409 (0.0422)	0.127 (0.0973)	-0.0167 (0.0537)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends				
Observations	65,921	21,751	60,302	65,934	57,143

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Panel A presents the results from regression the outcome variable on the level of temperature and monsoon rainfall. Panel B presents the differential effects of temperature across labor regulation environments. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table 10: The Effects of Temperature on Manufacturing Firms – Regulated Firms

	log Output and Employment			
	Total Output	Items Produced	Employment (Contract)	Employment (Permanent)
Panel A: Net Effect				
Daily Average Temperature (°C)	-0.0101 (0.0341)	-0.0516 (0.0333)	0.0383 (0.0236)	-0.0163 (0.0114)
Panel B: Differential Effect				
Daily Average Temperature (°C)	-0.0971* (0.0540)	-0.0497** (0.0220)	-0.170** (0.0667)	0.00283 (0.0382)
Temperature × Flexible	0.153* (0.0880)	0.0588* (0.0337)	0.211** (0.104)	0.0626 (0.0505)
Rainfall Controls	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends			
Observations	36,985	36,985	18,712	35,818

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Panel A presents the results from regression the outcome variable on the level of temperature and monsoon rainfall. Panel B presents the differential effects of temperature across labor regulation environments. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table 11: The Effects of Temperature on Manufacturing Firms – Regulated Firms

	log Wages and Productivity				
	Avg. Day Wage (Contract)	Avg. Day Wage (Permanent)	Output per Worker	TFPR	TFPR (CES)
Panel A: Net Effect					
Daily Average Temperature (°C)	-0.0299 (0.0299)	-0.0413** (0.0178)	-0.0434** (0.0184)	-0.0301* (0.0159)	-0.0299*** (0.0110)
Panel B: Differential Effect					
Daily Average Temperature (°C)	0.0335 (0.0333)	-0.0774*** (0.0221)	-0.103** (0.0513)	-0.0958*** (0.0299)	-0.100*** (0.0313)
Temperature × Flexible	-0.113** (0.0495)	0.0838** (0.0352)	0.128 (0.0838)	0.0969** (0.0438)	0.101** (0.0446)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends				
Observations	18,712	35,818	36,985	33,440	33,464

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Panel A presents the results from regression the outcome variable on the level of temperature and monsoon rainfall. Panel B presents the differential effects of temperature across labor regulation environments. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table 12: Additional Manufacturing Firm Outcomes – Regulated Firms

	log Capital, Management, and Entry				
	Capital	Capital Depreciation	Employment Managers	Day Wage Managers	Number of Plants
Panel A: Net Effect					
Daily Average Temperature (°C)	0.0571 (0.0442)	0.0329 (0.0263)	0.0323 (0.0220)	-0.0240* (0.0144)	0.00677 (0.00646)
Panel B: Differential Effect					
Daily Average Temperature (°C)	0.104 (0.0730)	0.0595 (0.0530)	-0.00464 (0.0442)	-0.0358 (0.0315)	0.00179 (0.0156)
Temperature × Flexible	-0.0830 (0.114)	-0.0482 (0.0823)	0.0651 (0.0718)	0.0208 (0.0496)	0.00879 (0.0242)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends				
Observations	36,810	29,454	36,550	36,550	36,985

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table 13: The Effects of Temperature on GDP

	Total GDP	Agricultural GDP	Services GDP	Manufacturing GDP	Construction GDP
Daily Average Temperature °C	-0.0263* (0.0136)	-0.116** (0.0571)	-0.0257* (0.0144)	-0.0120 (0.00963)	0.0183 (0.0232)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	District, Year, and State-Year Time Trends				
Observations	3,432	3,432	3,432	3,432	3,432

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. All dependent variables are in logs. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table 14: Counterfactual Estimates

	Baseline	Shutting Down Labor Reallocation		No adverse Temperature Effects		
	(1)	(2)	(3)	(4)	5	6
Informal (34%)	-18.3%	-18.3%	-18.3%	-18.3%	-18.3%	-3%
Unregulated Formal (44%)	8.8%	8.8%	-6.5%	8.8	24.1%	24.1%
Regulated Formal (22%)	-1.01%	-15.3%×Flexibility	-15.3%×Flexibility	15.3%	15.3%	15.3%
Total Manufacturing Effect	-2.57%	-4.58%	-11.32%	1.01%	7.74%	12.95%
Total Effect (Aggregate)	-3.03%	-3.31%	-4.25%	-2.53%	-1.59%	-0.86%
Change (%)	–	9.24%	40.26%	-16.50%	-47.52%	-71.67%

Notes: Column 1 (Baseline) provides a decomposition of the effect of a 1°C increase in temperature on manufacturing GDP decomposed into the regulated and unregulated formal manufacturing sector, using the estimated effects of a 1°C increase in temperature on firm-level output, and the informal sector, whereby the effect is the residual effect of a 1°C increase in temperature on firms in the informal sector to produce the estimated effect on manufacturing GDP. Columns 2, and 3 consider the effects of increasing the rigidity of the labor market environment to the level of West Bengal (the most Pro-Worker State). Column 2 increases the rigidity within the regulated formal manufacturing sector, and column 3 increases the rigidity in both the regulated and unregulated formal manufacturing sector, equivalent to expanding the coverage of the IDA. Columns 4, 5 and 6 consider the consequences of shutting down the adverse effects of temperature on manufacturing. Column 4 turns off the adverse effects of temperature for firms in the regulated formal manufacturing sector. Column 5 turns off the adverse effects of temperature for firms in the regulated and unregulated formal manufacturing sector (under the assumption that the adverse effects are constant across these two sectors). Column 6 turns off the adverse effects of temperature for firms in the formal and informal sector (under the assumption that the adverse effects are constant across these three sub-sectors).

Online Appendices – Not for Publication

A Theory Appendix

This appendix presents a simple 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).[28] Given prices in sector j, p_{ij} and total income w_iL_i, each worker maximises

$$U_i = (C_{ia} - \bar{a})^{\alpha} {C_{im}}^{1-\alpha} \tag{3}$$

which they maximise subject to their budget constraint,

$$p_{ia}C_{ia} + p_{im}C_{im} \leq L_iw_i \tag{4}$$

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.[29] I assume that all regions have access to the same technology and so

[28] 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).

[29] 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. Consequently, I drop the locational subscript unless necessary.

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

$$Y_j = A_j F_j(L_j) \tag{5}$$

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. Consequently, as market clearing requires that $L_a + L_m = L$, the marginal productivity of labor will be equalised across sectors,

$$p_a A_a F_a{}'(L_a) = w = p_m A_m F_m{}'(L_m) \tag{6}$$

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,

$$\begin{aligned} C_a &= A_a F_a(L_a) \\ C_m &= A_m F_m(L_m) \end{aligned} \tag{7}$$

Maximisation of equation 3 implies that each worker consumes agricultural goods such that,

$$p_a C_a = \bar{a} + \frac{\alpha p_m C_m}{1-\alpha} \tag{8}$$

Combining this result with the profit maximisation condition (equation 6), the labor market clearing condition ($L_m = 1 - L_a$), and the fact that total production must equal total consumption yields,

$$\Omega(L_m) = \frac{\bar{a}}{A_a} \tag{9}$$

where,

$$\Omega(L_m) \equiv F_m(L_m) - \frac{F_m{}'(L_m)F_a(1-L_a)}{F_a{}'(1-L_a)} \tag{10}$$

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

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

$$L_m = \Omega^{-1}\left(\frac{\bar{a}}{A_a}\right) \tag{11}$$

As preferences are non-homothetic the demand for agricultural goods (food) decreases as income increases (Engel's law). Consequently, 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. Consequently, 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,

$$p_a A_{i'a} F_{i'a}{}'(L_{i'a}) = p_m A_{i'm} F_{i'm}{}'(L_{i'm}) \tag{12}$$

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 6 and 12. Taking the ratio of these equations provides the following equality,

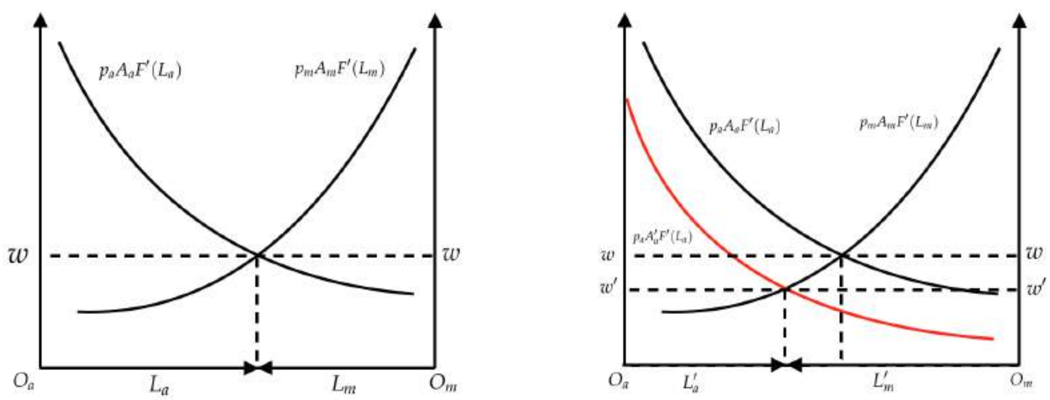
$$\frac{F_{im}{}'(L_{im}}{F_{ia}{}'(L_{ia})} = \frac{A_{ia}A_{i'm}}{A_{i'a}A_{im}} \frac{F_{i'm}{}'(L_{i'm})}{F_{i'a}{}'(L_{i'a})} \tag{13}$$

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

$$L_{im} \gtreqless L_{ia} \quad iff \quad \frac{A_{i'a}}{A_{i'm}} \gtreqless \frac{A_{ia}}{A_{im}} \tag{14}$$

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 figure 1

Figure 1: 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 aribtrage opportunities as before; however, the local price is bounded by a trade cost δ. Consequently, 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., $\bar{p}_j < p_j^A/\delta$. Consequently, 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., $\frac{\bar{p}_j}{\delta} \leq p_j^A \leq \bar{p}_j\delta$.

B Data appendix

B.1 Agricultural Data Appendix

This section provides additional details on the Agriculture data used in section III.

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. Figures 1 provides summary statistics for the 12 crops used.

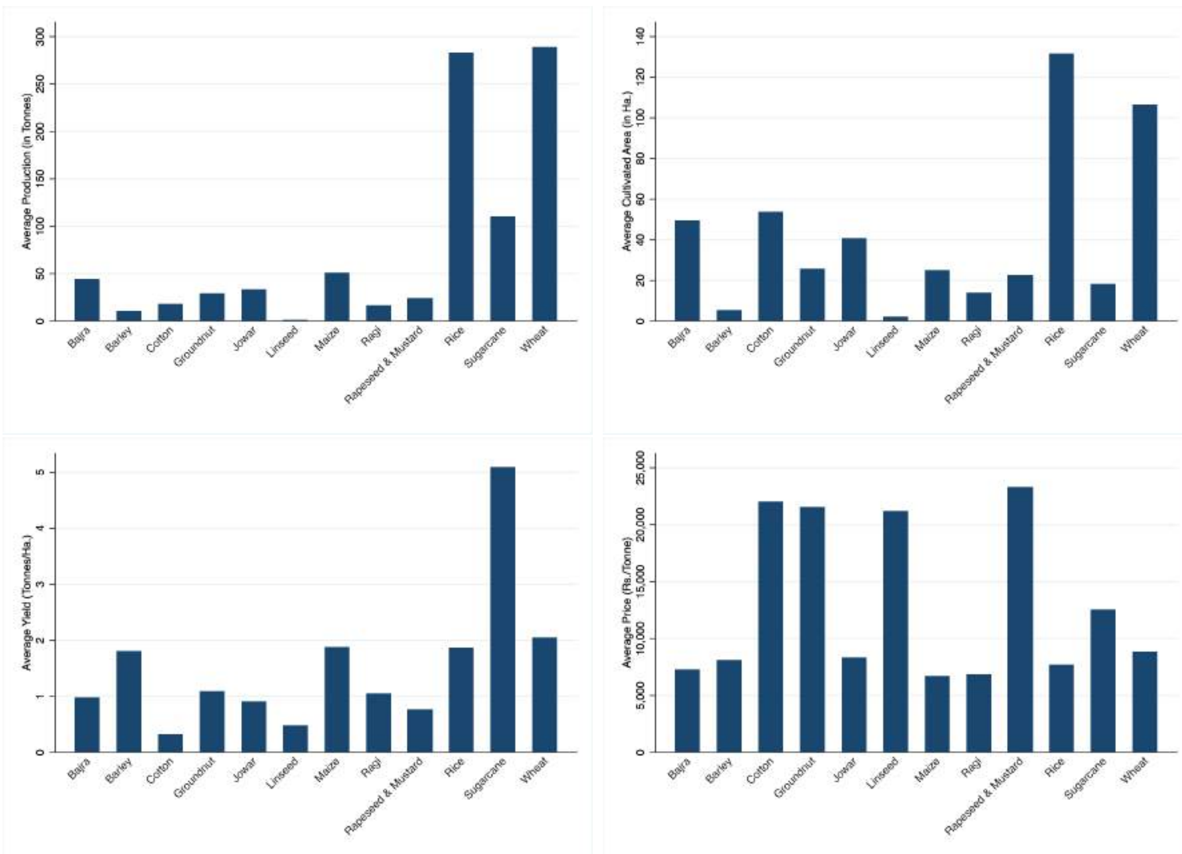


Figure 1: Average: (TL) Production; (TR) Cultivated Land Area; (BL) Yield; (BR) Price (2001 Rs.)

We observe from the figures that both Rice and Wheat are the most produced crops in terms of cultivated land area and total production (figure 1) and that they also comprise the largest share of production and cultivated land area within-district (figure 2). However, in terms of yields sugarcane is show to have one of the highest yields and has the largest share of yields within-district (figure 2).

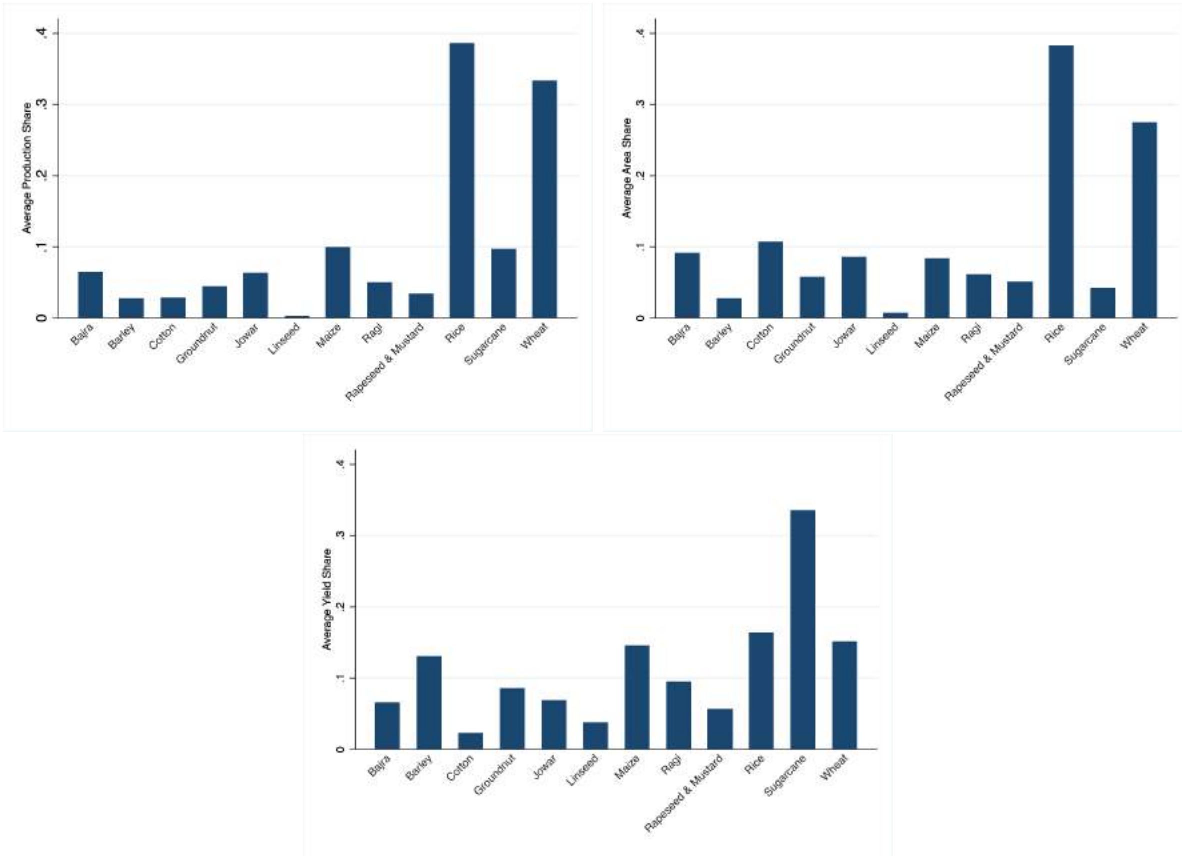


Figure 2: District Shares of: (TL) Agricultural Production; (TR) Agricultural Cultivated Land; (B) Agricultural Yields

B.2 NSS Data Appendix

This section provides additional details on the NSS Employment and Unemployment surveys used in section III. The National Sample Survey Organisation (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 average day wage 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.

As one might expect agricultural employment is largely focused in rural areas accounting for an average of 60% of rural employment during this period. However, employment manufacturing and services account collectively for just over 25% of rural employment. By

Table B1: Labor Force Shares in India (2001–2007)

	Rural	Urban	Combined
Agriculture	59.7%	7.8%	42.7%
Manufacturing	14.6%	40%	22.9%
Services	11.5%	35.7%	19.4%
Construction	5.9%	7.6%	6.5%
Unemployment	8.1%	8.6%	8.3%

contrast, in urban areas manufacturing and services account for close to 75% of employment. 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 peri-urbanization (see Colmer (2015) for a more detailed discussion and review of this literature). 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. (forthcoming) and Ghani et al. (2014) also provide supporting evidence for this process in India. Desmet et al. (forthcoming) 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 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 sectors is becoming more rural; however, in practice a lot of this movement is likely sub-urbanization, rather than ruralisation, 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 costs. 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 presented in rural and urban areas respectively. 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.

B.3 Weather Data Appendix

This section provides additional details on the weather data used throughout this paper.

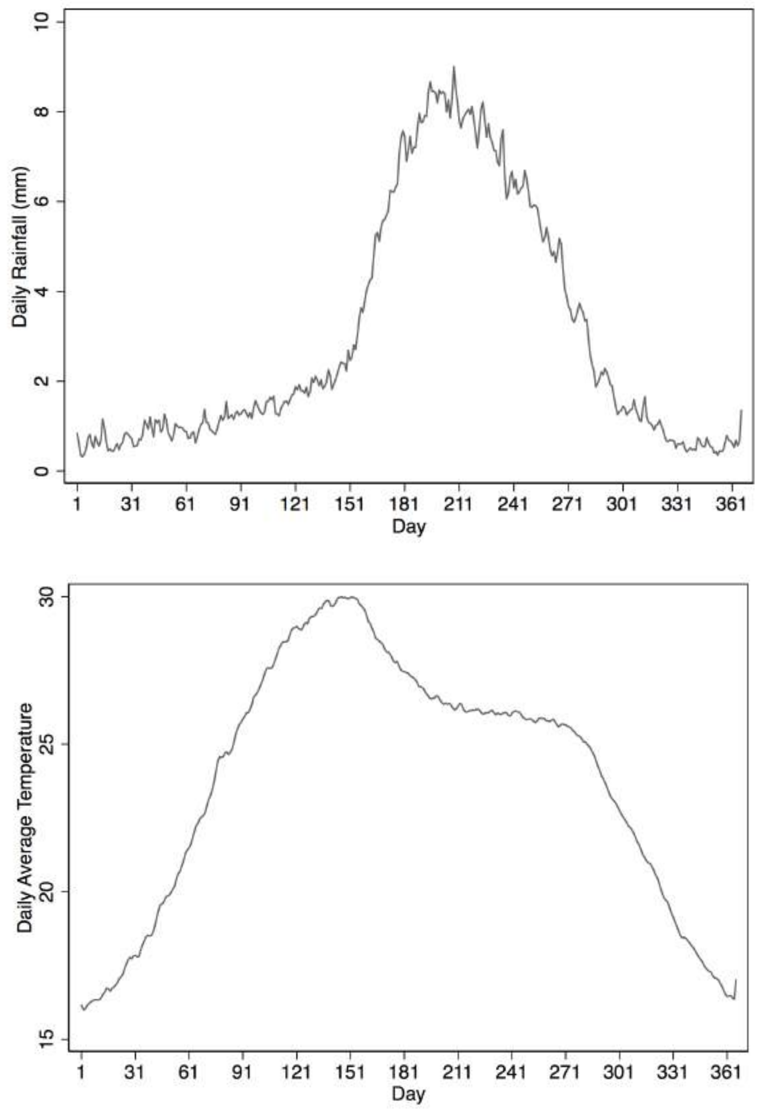


Figure 3: Intra-Annual Weather Variation

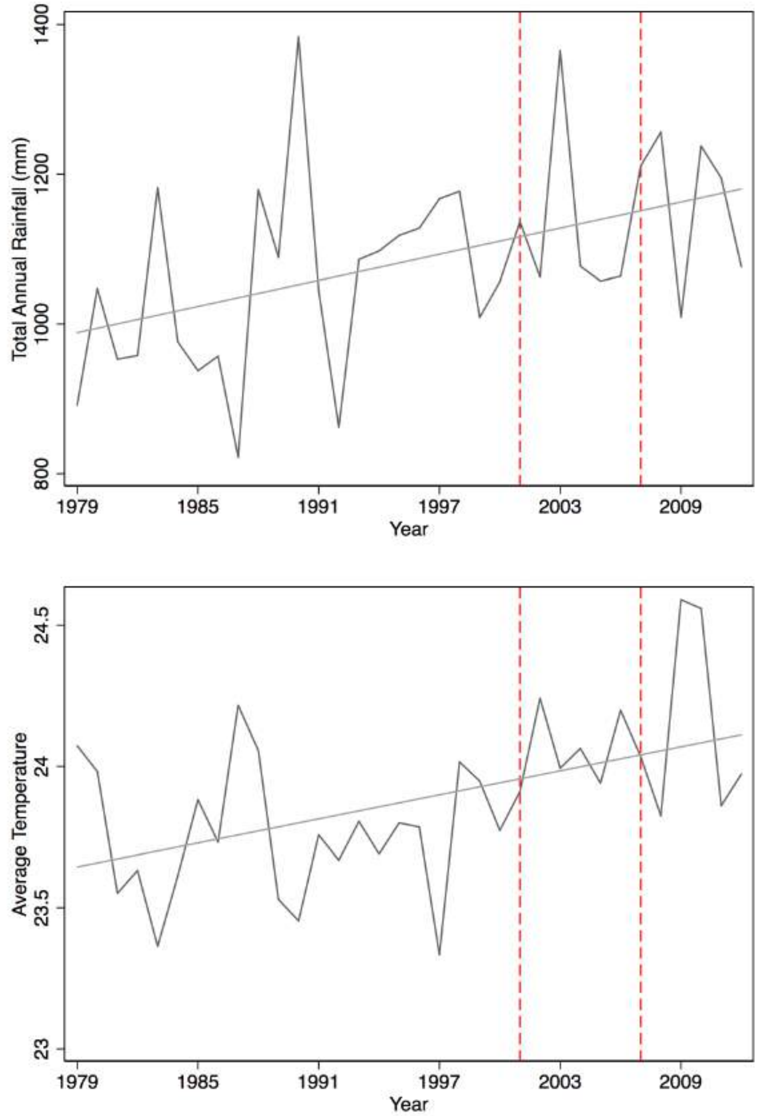


Figure 4: Inter-Annual Weather Variation

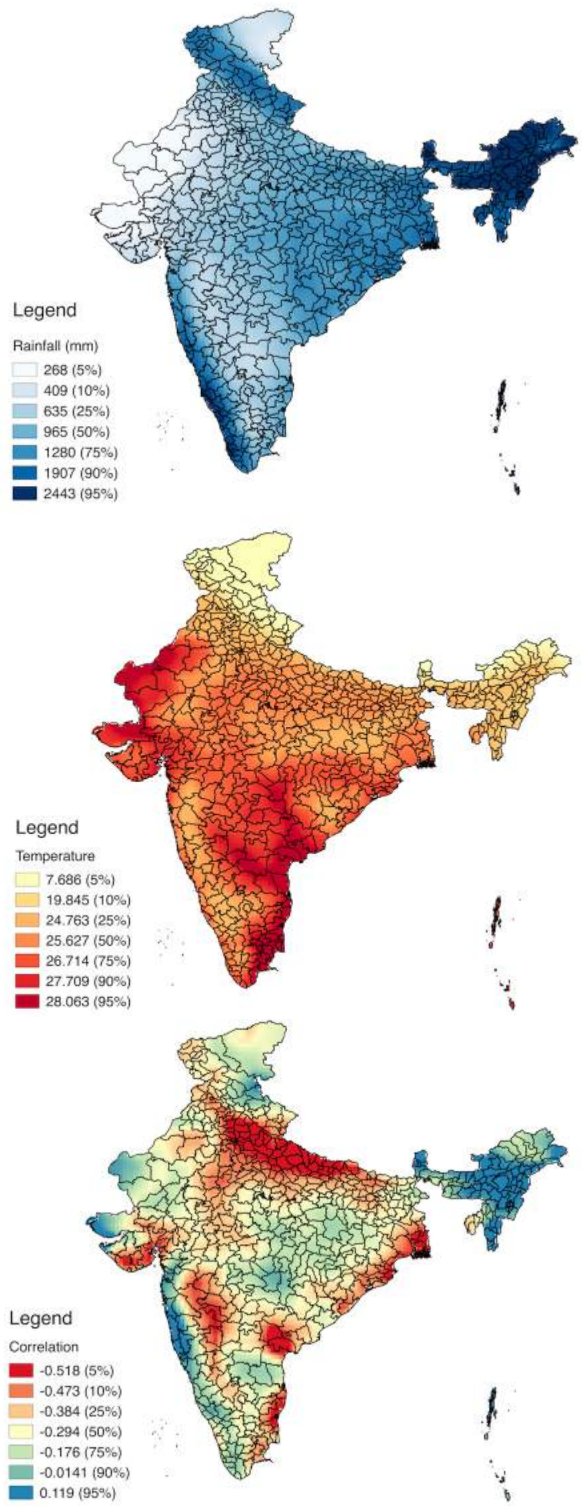


Figure 5: Spatial Weather Variation

B.4 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 before apply the following cleaning processes, summarised in table B2 With this initial sample I begin by dropping all plants that are outside of the manufacturing sector, closed. In addition, I remove all observations with missing or zero total output data due to the importance of the revenue and productivity results. I then combine this data with the weather data taken from the ERA-Interim Reanalysis Data archive. Finally, I drop Union Territories and remove all districts with zero agricultural production. This is due to the focus on agricultural productivity shocks as a driver of labor reallocation.

All financial amounts are deflated to constant 2001-02 Rupees.[30] 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.[31] 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. Fuel and Electricity costs are deflated by the price index for "Fuel, Power, Light, and Lubricants". Capital is deflated by an implied national deflator calculated from "Table 13: Sector-wise Gross Captial Formation" from the Reserve Bank of India's Handbook of Statistics on the India Economy.[32] Wage costs are deflated using a national GDP deflator.

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

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

[32]Available from http://www.rbi.org.in

Table B2: ASI Sample Selection

Action Taken	Observations Dropped	Final Sample
Initial Sample	-	371,383
Drop Sectors Outside of Manufacturing	22,645	348,739
Drop Closed Plants	90,115	258,624
Merge Weather Data	16,196	235,679
Drop Union Territories	1,727	233,952
Drop if Employment < 10	56,269	177,683
Drop if Employment < 20 & No Electricity	1,139	176,544
Drop Total Output Zero or Missing	19,989	156,555
Merge with Deflators	9	156,546
Keep Agricultural Districts	53,273	103,273
Plants-Year Observations Above the Threshold	-	36,985
Plants-Year Observations Below the Threshold	-	65,934

C Productivity Estimation

In what follows I provide an explicit model of TFPR, in the context of a profit-maximising firm.

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

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

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

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:

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

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 $X \in \{K, L, M, E\}$. 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 β_L, β_M, and β_E using median regression for each industry-year cell.

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

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:

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

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},

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

C.1 Allowing for Differences in the Elasticity of Substitution Within Labor

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

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

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

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 permanent 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.

Given that contract and permanent labor markets are segmented, i.e., we observe no increase in the number of permanent workers, this suggests that the tasks that the casual entrants and permanent 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 the new entrants into casual positions and the incumbent permanent workers. If $\sigma < 1$ the new entrant casual workers and incumbent permanent workers engage in tasks that are complementary in production. If $\sigma > 1$ then these workers engage in tasks that are substitutable in the production process.

$$\sigma \propto \frac{\partial \log w_m^p}{\partial Temperature} / \frac{\partial \log L_m^c}{\partial Temperature} = \frac{\partial \log w_m^p}{\partial \log L_m^c} = 0.39 \tag{15}$$

These results suggest that a 1% increase in the number of casual workers, employed out of agriculture, is associated with a 0.39% increase in the average wage of permanent 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 permanent workers in the regulated Indian manufacturing sector 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.

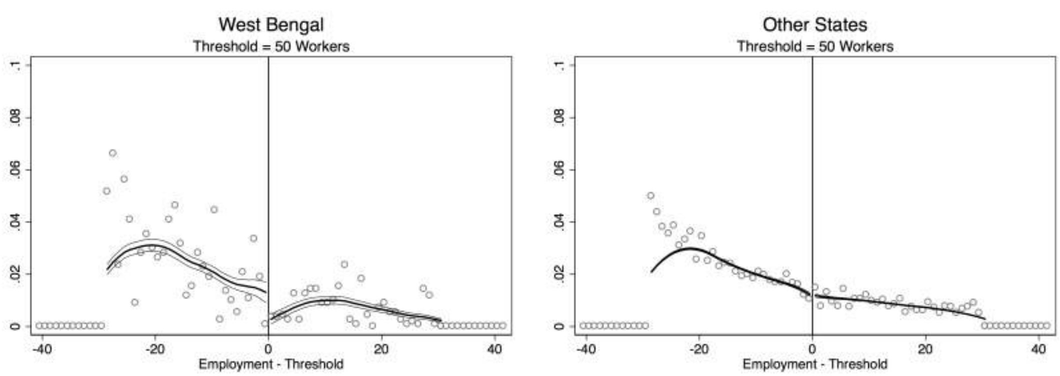
D The Labor Regulation Environment – Supporting Evidence

This appendix provides supporting evidence for the identification strategy that exploits spatial variation and firm-level exposure to India's labor regulation environment.

D.1 Bunching in the Firm-Size Distribution

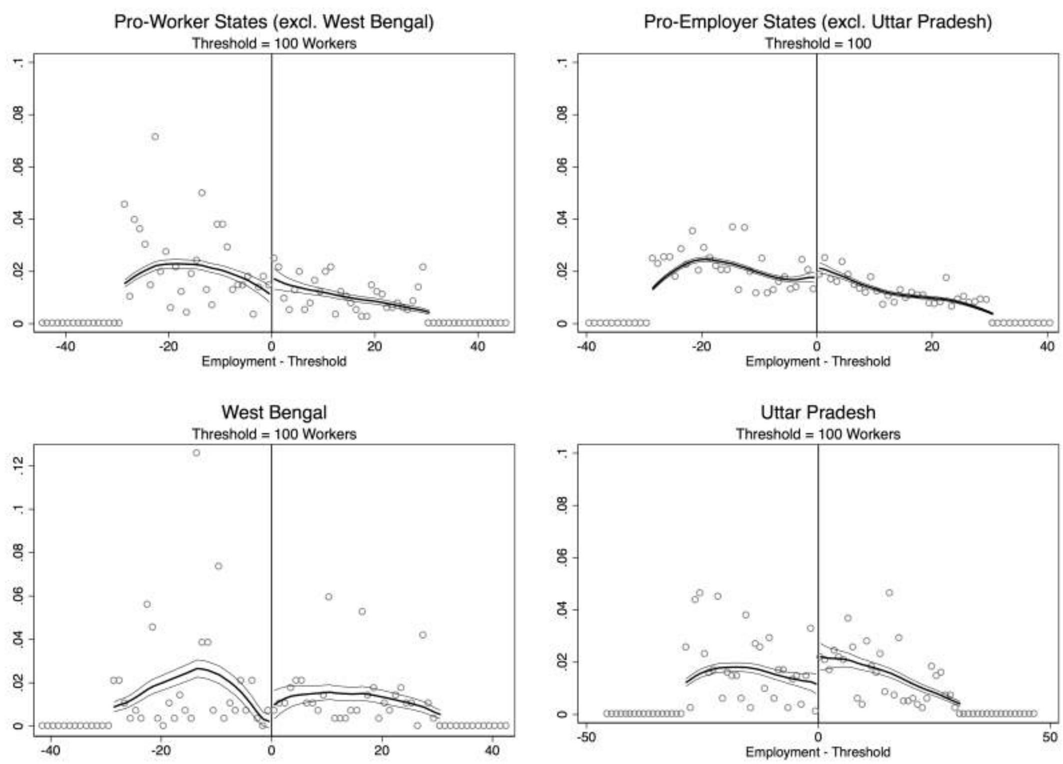
First I examine the degree to which there is bunching in the firm-size distribution, exploiting differences in the incentives that firms face across different states as well as differences in the regulatory thresholds. Previous work has argued that there little evidence of bunching in the firm-size distribution associated with the Industrial Disputes Act (Hsieh and Olken, 2013). However, I demonstrate that the absence of bunching in this previous work arises due to three considerations: 1) applying a nationwide threshold of 100, rather than state-specific thresholds; 2) not distinguishing between pro-worker (where bunching is more likely) and pro-employer states (where bunching is less likely); 3) conflation between the effect of the IDA and changes in the sampling schedule around the modal threshold of 100 workers. In the results presented below I use the year 2007 as this has the largest sample to maximize power; however, results are robust to other years. Furthermore, all results account for the sampling weights in order not to minimize the conflation of changes in the sample schedule with changes arising from the IDA.

I demonstrate that in West Bengal, arguably the state with the most rigid labor regulation environment, that there is a bunching of firms just below the regulatory threshold of 50 workers. However, there is no bunching for the other states around this threshold, in support of the identification strategy.

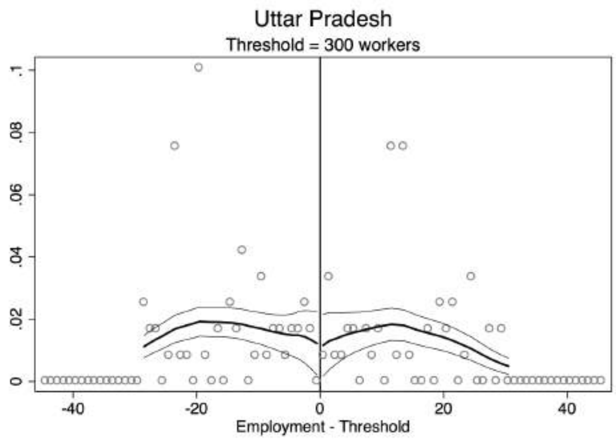


Identifying bunching around the regulatory threshold of 100 is more challenging as this coincides with a change in the sampling scheme of the ASI, in which there is an oversampling

above this threshold. Despite accounting for sampling weights, we observe that there is limited bunching just *above* the regulatory threshold. This is the complete opposite to what one should expect. In rigid states there should be bunching to the left of the threshold, and for flexible states this bunching should be smaller, consistent with the observed bunching in West Bengal at the 50 worker threshold. Due to the fact that the sampling scheme of the ASI coincides with the regulatory threshold it is impossible to identify or rule out bunching at this level. However, it is interesting to note that we observe stronger bunching to the right of a placebo regulatory threshold of 100 for West Bengal and Uttar Pradesh, where there is no actual threshold in place. This provides support for the conclusion that the sampling scheme of the ASI interferes with the identification. The limited bunching to the right of the regulatory threshold in the other states, suggests that in the absence of the change in the sampling scheme we would observe some though limited bunching to the left of the regulatory threshold at 100 workers.



In further support of the assumption that the sampling scheme interferes with the identification strategy I don't find any differences around the regulatory threshold of 300 in "flexible" Uttar Pradesh. This suggests that there isn't anything fundamentally related to the labor regulation environment in flexible states that would result in bunching to the right of the regulatory threshold.



Collectively, this evidence suggests that by accounting for state-specific thresholds and distinguishing between flexible and rigid labor markets (as opposed to grouping all states), one can uncover evidence of bunching in the firm-size distribution associated with the Industrial Disputes Act. Consequently, this suggests that regulated firms may well face differential incentives in the propensity to hire workers in response to transitory labor demand shocks.

D.2 Temperature isn't correlated with Amendments made to the Industrial Disputes Act

In this section I demonstrate that temperature didn't appear to be a determinant of amendments made to the IDA, using data on the year and state of amendments made. Given that the weather data is only available from 1979, I am unable to look at amendments prior to this. Between 1979 and 1995 18 amendments out of a total of 39 were made.

The results suggest that temperature is not correlated with the introduction, direction, or magnitude or amendments made. Even the largest coefficient in column (3) accounting for the magnitude of amendment changes, suggests that a 1 standard deviation increase in temperature is associated with at most an additional 0.022 pro-worker amendments. Rainfall does not appear to be correlated with whether an amendment was mode or the direction of amendment changes on average. However, when the magnitude changes are taken into account a one standard deviation increase in rainfall is associated with an additional 0.12

Table D1: The Effects of Temperature on Amendments to the Industrial Disputes Act

	(1) Any Change	(2) Relative Change	(3) Total Change
Daily Average Temperature (°C)	0.00107	0.0310	0.0682
	(0.0584)	(0.0530)	(0.119)
Monsoon Rainfall (100mm)	0.0167	0.0176	0.0677**
	(0.0128)	(0.0109)	(0.0263)
Observations	272	272	272

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. The unit of analysis is a state-year. Any Change relates to whether an amendment was made. Relative Change accounts for the direction of any amendment changes, i.e., whether it was pro-worker or pro-employer. Total Change accounts for the magnitude and direction of the change, e.g., if 3 pro-worker amendments were made a value of -3 would be assigned to that state in that year. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

pro-worker amendments. While statistically significant, the magnitude of this effect is not particularly large. Most importantly, this does not affect the inference associated with the evaluation of temperature.

D.3 The Effect of the Labor Regulation Environment on Unregulated Sectors

Finally, I explore whether there are any noticeable differences in temperature effects across labor regulation environments through an examination of unregulated sectors such as agriculture, services and construction. I find limited evidence to suggest that there are significant differences in the effects temperature effects across labor regulation environments when looking at these unregulated sectors, or the manufacturing broadly defined to include both the formal sector (those above and below the regulatory threshold) and the informal sector. These results provide further support for the identification strategy as they suggest that there are no first-order spatial differences between the collection of states that make up rigid and flexible labor regulation environments, that are likely to bias the estimated effects on regulated firms.

Table D2: The Differential Effect of Temperature on Real GDP - By Sector (2001 – 2012)

	(1) Total	(2) Agriculture	(3) Manufacturing	(4) Services	(5) Construction
Daily Average Temperature (°C)	-0.00221 (0.0145)	-0.0939* (0.0543)	-0.0759** (0.0344)	0.0113 (0.0166)	0.112** (0.0503)
Temperature × Flexibility	-0.0353 (0.0226)	-0.0324 (0.0798)	0.0736 (0.0452)	-0.0342 (0.0236)	-0.137* (0.0709)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	District, Year, and State-Year Time Trends				
Observations	3,432	3,432	3,432	3,432	3,432

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

E Additional Results and Robustness Tests

This appendix provides a series of additional results and robustness tests to support of the main results presented in the paper.

E.1 Non-Linearities in the Temperature Schedule

In this section I explore the degree to which there are non-linearities in the temperature schedule. A large literature in agricultural science has demonstrated that the relationship between agricultural yields and weather is highly nonlinear (Schlenker and Roberts, 2009; Auffhammer and Schlenker, 2014). To account for these non-linearities I explore 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,

$$GDD_{d;t_l;t_h} = \begin{cases} 0 \text{ if } t_d \leq t_l \\ t_d - t_l \text{ if } t_l < t_d < t_h \\ t_h - t_l \text{ if } t_h \leq t_d \end{cases} \tag{16}$$

These daily measures are then summed over the period of interest.[33] 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, 2015). 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 both omitted variable concerns, as 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,

[33] 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.

$$f(w_{dt}) = \beta_1 GDD_{dt;t_l;t_h} + \beta_2 GDD_{dt;t_h;\infty} + \beta_3 Rain_{dt} \quad (17)$$

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 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 17°C. This kink-point is applied to all results for consistency.

The second approach explores the effects of non-linearities in the temperature schedule 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 between are 2°C wide. Using this approach I model weather as a flexible function of temperature and precipitation,

$$f(w_{dt}) = \sum_{j=1}^{10} \beta_j Temp_{dtj} + \beta_3 Rain_{dt} \quad (18)$$

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 they 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.

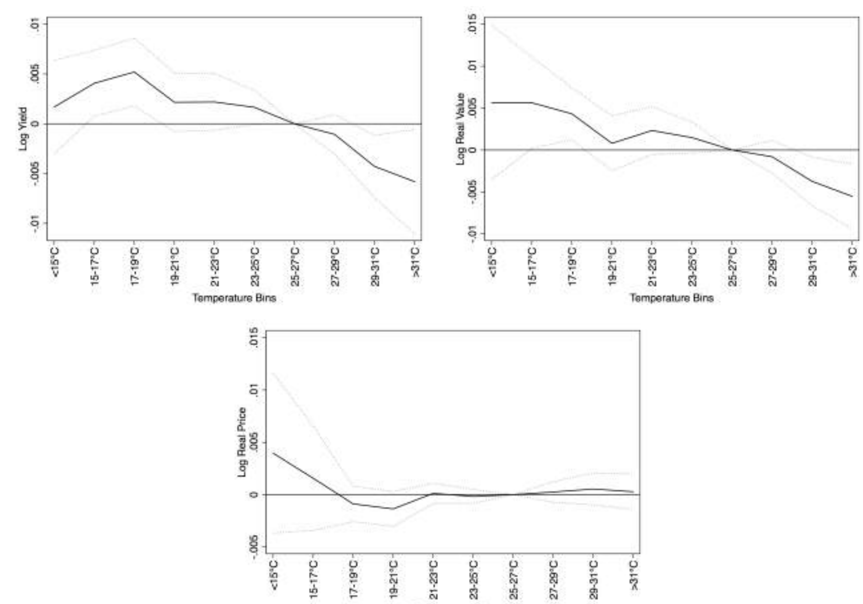
E.1.1 Agricultural Outcomes

Table E1: The Effects of Daily Temperature on Agricultural Outcomes

	Agricultural Outcomes		
	Log Value (All Crops)	Log Yield (All Crops)	Log Price (All Crops)
Degree Days (10 days) $t_L = 17, t_H = \infty$	-0.00757*** (0.00206)	-0.00728*** (0.00180)	0.000289 (0.000579)
Degree Days (10 days) $t_L = 0, t_H = 17$	0.00394 (0.00369)	-0.00437 (0.00475)	-0.00831** (0.00395)
Rainfall Controls	Yes	Yes	Yes
Fixed Effects	Crop × District, Crop × Year and State-Year Time Trends		
Observations	9,813	9,813	9,813

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 modelled in Conley (1999) and serial correlation (1-year) as modelled 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 1: The Effects of Daily Temperature on Agricultural Outcomes



E.1.2 Employment and Wage Outcomes

Table E2: The Effects of Daily Temperature on Wages

	(1) AGRICULTURE	(2) MANUFACTURING	(3) SERVICES	(4) CONSTRUCTION
DEGREE DAYS (10 days)	-0.000918	-0.00156	-0.000136	-0.000518
$t_L = 17, t_H = \infty$	(0.000734)	(0.00114)	(0.00201)	(0.00119)
DEGREE DAYS (10 days)	0.000373	0.00122	-0.000593	0.00118
$t_L = 0, t_H = 17$	(0.00258)	(0.00336)	(0.00357)	(0.00222)
RAINFALL CONTROLS	YES	YES	YES	YES
FIXED EFFECTS	DISTRICT, YEAR AND STATE-YEAR TIME TRENDS			
Observations	1,067	1068	1099	1035

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 modelled in Conley (1999) and serial correlation (1-year) as modelled 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 2: The Effects of Daily Temperature on Wages

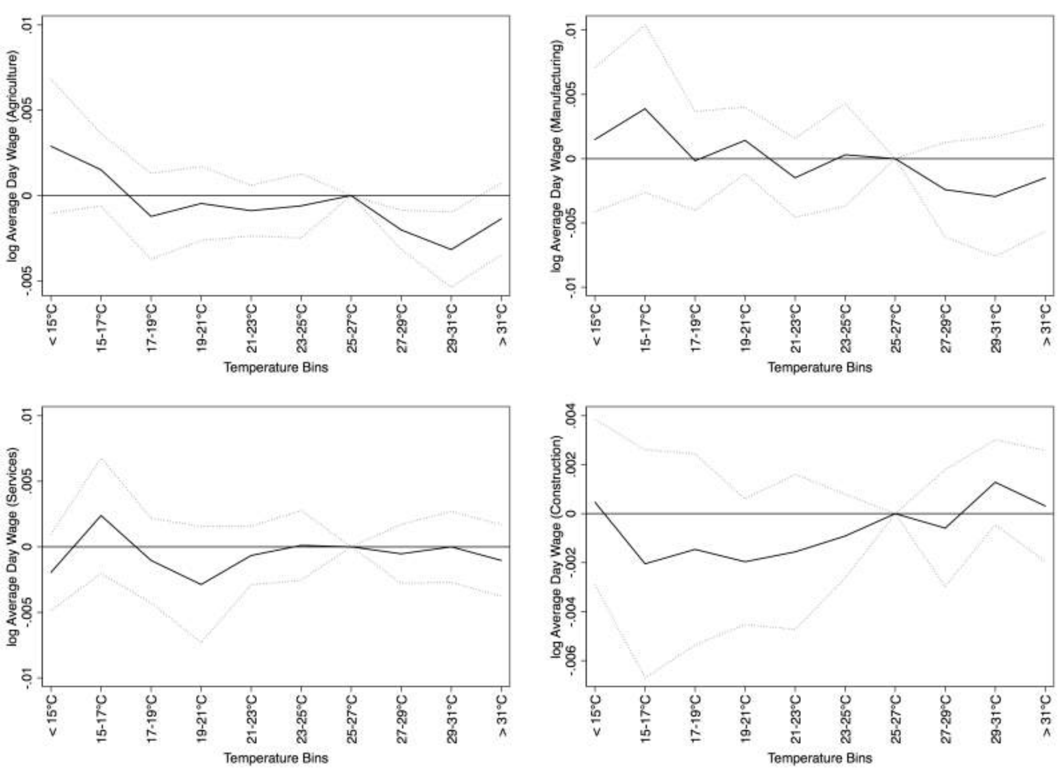
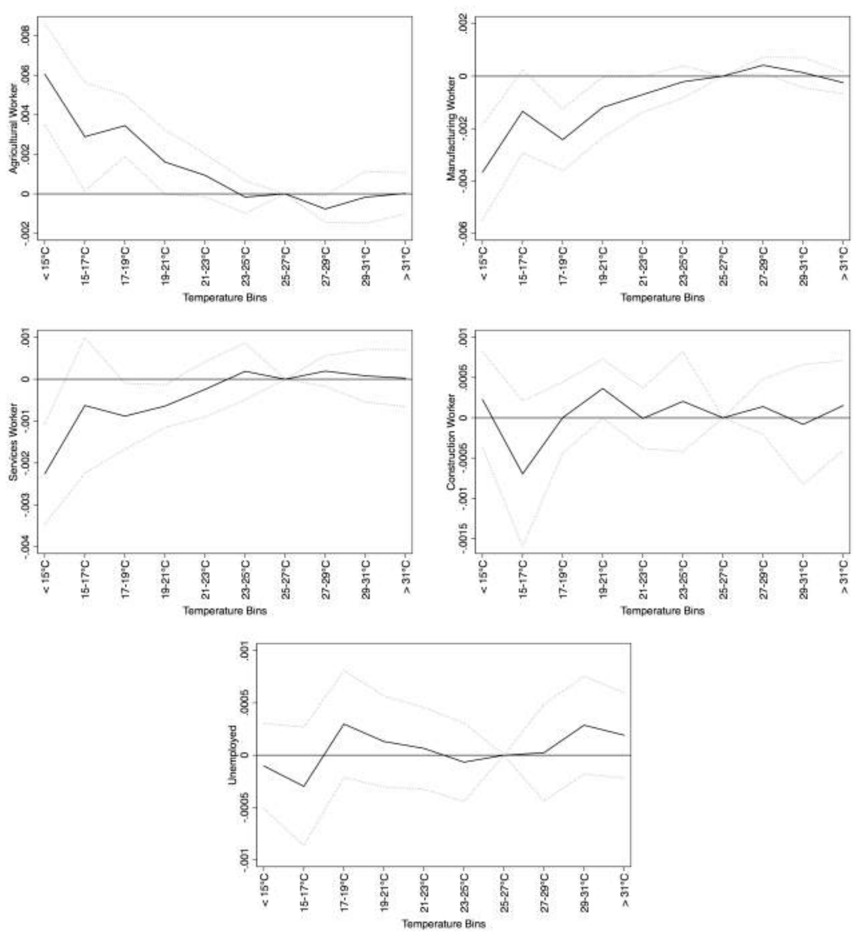


Table E3: The Effects of Daily Temperature on Employment

	(1) Agriculture	(2) Manufacturing	(3) Services	(4) Construction	(5) Unemployed
Degree Days (10 days)	-0.00264***	0.00163***	0.000796***	0.000107	0.000114
$t_L = 17, t_H = \infty$	(0.000648)	(0.000436)	(0.000259)	(0.000183)	(0.000145)
Degree Days (10 days)	-0.00435***	0.00269***	0.00169**	0.0000111	-0.0000398
$t_L = 0, t_H = 17$	(0.00134)	(0.000657)	(0.000759)	(0.000355)	(0.000359)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	District, Year, and State-Year Time Trends				
Observations	1,105	1,105	1,105	1,105	1,105

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 modelled in Conley (1999) and serial correlation (1-year) as modelled 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 3: The Effects of Daily Temperature on Employment



E.1.3 Manufacturing Firms

Table E4: The Effects of Daily Temperature on Manufacturing Outcomes (Regulated)

	Total Output	Employment Contract	Employment Permanent	Day Wage Contract	Day Wage Permanent
Degree Days (10 days)	-0.00250	-0.00396*	0.000167	0.00120	-0.00226***
$t_L = 17, t_H = \infty$	(0.00162)	(0.00204)	(0.00110)	(0.000992)	(0.000621)
DD High × Flexibility	0.00429*	0.00556*	0.00222	-0.00331**	0.00221**
	(0.00244)	(0.00302)	(0.00142)	(0.00141)	(0.000994)
Degree Days (10 days)	-0.00546	-0.0114	-0.00611	-0.00663	-0.000463
$t_L = 0, t_H = 17$	(0.00730)	(0.0134)	(0.00514)	(0.00540)	(0.00308)
DD Low × Flexibility	0.00584	0.00990	0.00673	0.00810	0.00221
	(0.0114)	(0.0193)	(0.00780)	(0.00793)	(0.00448)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends				
Observations	36,985	18,712	35,818	18,712	35,818

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,800km) as modelled in Conley (1999) and serial correlation (1-year) as modelled 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.

Table E5: The Effects of Daily Temperature on Manufacturing Outcomes (Regulated)

	Output Per Worker	TFPR	TFPR (CES)	Items Produced
Degree Days (10 days)	-0.00263*	-0.00214**	-0.00222**	-0.00140**
$t_L = 17, t_H = \infty$	(0.00159)	(0.000886)	(0.000919)	(0.000693)
DD High × Flexibility	0.00346	0.00206*	0.00212*	0.00157
	(0.0244)	(0.0302)	(0.0142)	(0.0141)
Degree Days (10 days)	-0.000404	-0.000242	-0.000244	-0.000107
$t_L = 0, t_H = 17$	(0.000712)	(0.000388)	(0.000402)	(0.000296)
DD Low × Flexibility	0.000336	-0.0000634	-0.0000770	0.000251
	(0.00107)	(0.000596)	(0.000615)	(0.000444)
Rainfall Controls	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year and State-Year Time Trends			
Observations	36,985	33,445	33,464	36,985

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,800km) as modelled in Conley (1999) and serial correlation (1-year) as modelled 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.

Figure 4: The Effects of Daily Temperature on Manufacturing Outcomes (Regulated)

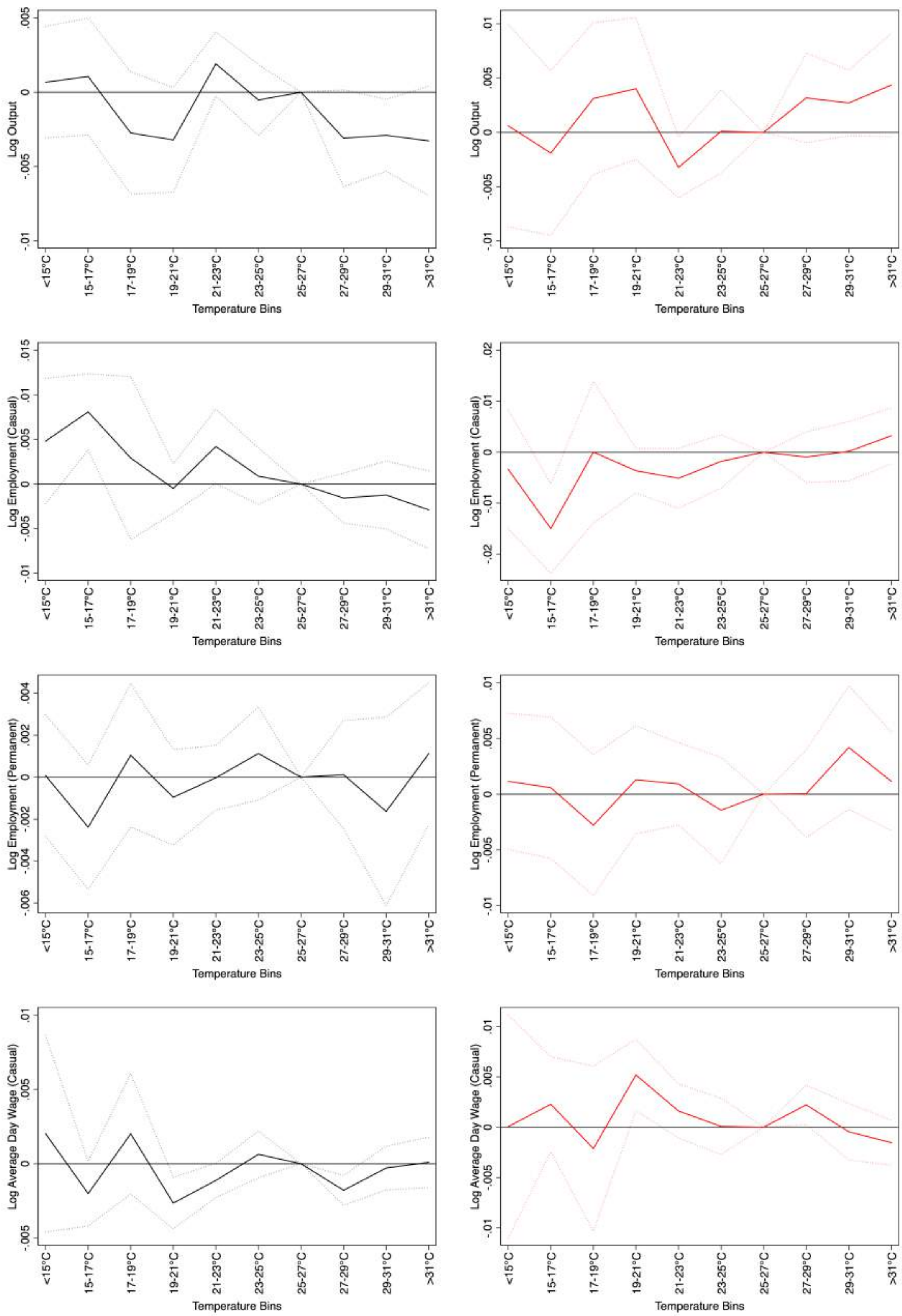
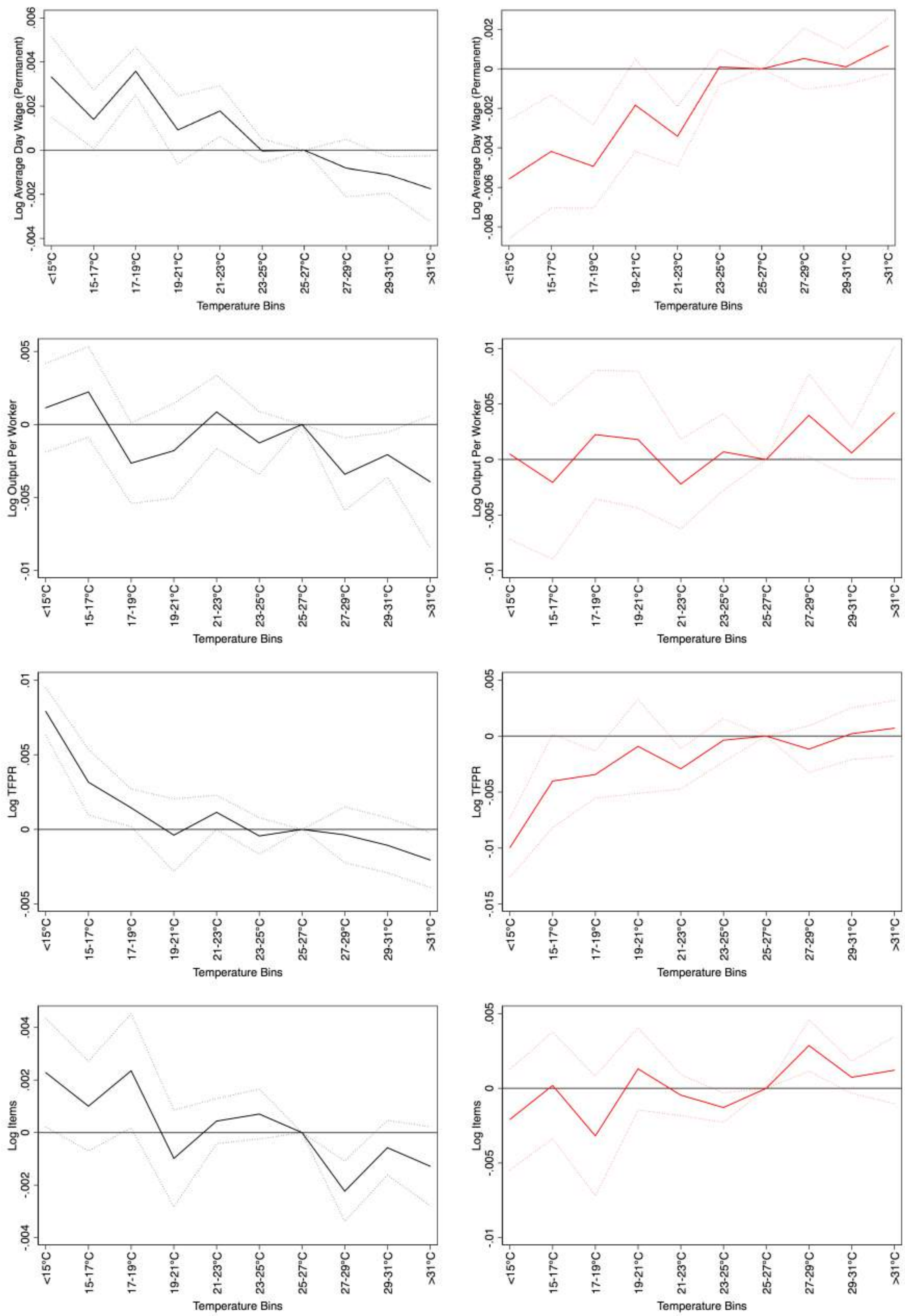


Figure 5: The Effects of Daily Temperature on Manufacturing Outcomes (Regulated)



E.2 Instrumental Variable Evidence

In this section I propose an Instrumental Variables strategy to support the basic identification strategy. As discussed, and demonstrated, in the main results, there are a number of channels through which temperature could affect manufacturing outcomes. Consequently, one cannot use temperature as an instrument for agricultural yields or employment to look at the effects of temperature on manufacturing through the labor reallocation channel, due to the clear violation of the exclusion restriction. However, if one believes that the labor regulation environment only moderates the effects of temperature through the labor reallocation channel then one can instrument the interaction between agricultural yields or employment and the labor regulation environment with the interaction of temperature and the labor regulation environment. This allows the level effect of temperature to continue serving its role in capturing the net effect of all remaining channels, while the interaction effect captures the labor reallocation channel.

Table E6 explores the first stages for this instrument that could be used on two endogenous regressors the share of workers who are agricultural laborers, and agricultural yields. In both cases increases in temperature in flexible labor market environments are associated with reductions in the share of employment and agricultural yields in flexible labor markets. However, the F-statistic is larger when the endogenous regressor is the interaction between labor market flexibility and agricultural yields. This may relate to the larger sample size due to the complete coverage of years.

Table E6: First Stage Estimates

	Ag. Worker Share × Flexible	log Yields × Flexible
Daily Average Temperature × Flexible	-16.225***	-0.350***
	(4.090)	(0.055)
Fixed Effects	Sector × District, Sector × Year and State-Year Time Trends	
Observations	20,300	36,686
Angrist-Pischke F-Stat	15.73	40.43

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. The years of observation are 2003, 2004, 2005 and 2007 for the agricultural laborer instrument as these are the years in which data is available from the NSS. Data for agricultural yields is available for all years. Standard errors are clustered at the state level.

Focussing on the stronger first-stage relationship I estimate second-stage relationships for manufacturing firm outcomes, using the interaction of log Yields and the flexibility of

the labor regulation environment as the endogenous regressor.[34] This gives an elasticity interpretation to the instrumented regressor and the outcome variables which are in log form. Consistent with the reduced form exercise in the main text I find that a reduction in agricultural yields in more flexible labor regulation markets is associated with an increase in output and contract workers, with a reduction in the wages of contract workers. In addition, the number of permanent workers is unchanged and the average wage of permanent workers increase. The estimated elasticity of substitution between contract and permanent workers using these estimates is 0.29, smaller than the reduced form measure (0.53), but still consistent with the premise that contract workers are complementary in the production process (Table E7). As in the reduced form results I also find that a reduction in agricultural yields in more flexible labor regulation markets is associated with increases in output per worker and the number of items produced, as well as noisily estimated increases in TFP (Table E8). Together these results provide suggestive evidence that the inflow of contract workers allow firms to move down the average cost curve, by allowing permanent workers to engage in more productive activities.

Table E7: Second Stage (log Yields × Flexible): The Effects of Daily Temperature on Manufacturing Outcomes (Regulated)

	log Output and Employment			
	Total Output	Items Produced	Employment (Contract)	Employment (Permanent)
Daily Average Temperature (°C)	-0.0622 (0.0424)	-0.0363** (0.0164)	-0.145*** (0.0398)	0.0174 (0.0327)
log Ag. Yields × Flexibility	-0.438** (0.195)	-0.168** (0.0802)	-0.806*** (0.256)	-0.176 (0.161)
Rainfall Controls	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends			
Observations	36,686	36,686	18,421	35,521

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,800km) as modelled in Conley (1999) and serial correlation (1-year) as modelled 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.

[34] Results are broadly robust to using the share of agricultural workers as the endogenous regressor presented in Tables E9 and E10.

Table E8: Second Stage (log Yields × Flexible): The Effects of Daily Temperature on Manufacturing Outcomes (Regulated)

	log Wages and Productivity				
	Avg. Day Wage (Contract)	Avg. Day Wage (Permanent)	Output Per Worker	TFPR	TFPR (CES)
Daily Average Temperature (°C)	0.0202 (0.0164)	-0.0578** (0.0228)	-0.0735** (0.0375)	-0.0737** (0.0330)	-0.0771** (0.0370)
log Ag. Yields × Flexibility	0.433** (0.175)	-0.236** (0.112)	-0.366** (0.183)	-0.277 (0.170)	-0.288 (0.188)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year and State-Year Time Trends				
Observations	18,421	35,521	36,686	33,137	33,163

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,800km) as modelled in Conley (1999) and serial correlation (1-year) as modelled 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.

Table E9: Second Stage (Ag. Laborer Share × Flexible): The Effects of Daily Temperature on Manufacturing Outcomes (Regulated)

	log Output and Employment			
	Total Output	Items Produced	Employment (Contract)	Employment (Permanent)
Daily Average Temperature (°C)	-0.0619* (0.0365)	-0.0548** (0.0258)	-0.258*** (0.0784)	0.0101 (0.0804)
Ag. Laborer Share × Flexibility	-0.877*** (0.311)	-0.770*** (0.299)	-1.760* (0.900)	-0.635 (0.846)
Rainfall Controls	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends			
Observations	20,300	20,300	10,190	19,615

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,800km) as modelled in Conley (1999) and serial correlation (1-year) as modelled 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.

Table E10: Second Stage (Ag. Laborer Share × Flexible): The Effects of Daily Temperature on Manufacturing Outcomes (Regulated)

	log Wages and Productivity				
	Avg. Day Wage (Contract)	Avg. Day Wage (Permanent)	Output Per Worker	TFPR	TFPR (CES)
Daily Average Temperature (°C)	0.0608***	-0.0496**	-0.0392	-0.0577	-0.0739
	(0.0184)	(0.0211)	(0.0482)	(0.0560)	(0.0631)
Ag. Laborer Share × Flexibility	0.847***	-0.485*	-0.377	-0.640	-0.750
	(0.319)	(0.259)	(0.558)	(0.473)	(0.537)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year and State-Year Time Trends				
Observations	10,190	19,615	20,300	18,366	18,380

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Standard errors are adjusted to reflect spatial dependence (up to 1,800km) as modelled in Conley (1999) and serial correlation (1-year) as modelled 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.

E.3 Alternative Definitions of the Labor Regulation Environment

In addition to the evidence in support of the identification strategy, I provide a series of robustness tests in support for the main results.

Table E11: Alternative Measures of the Labor Regulation Environment – (Neutral and Flexible Binary Variables)

	log Output and Employment			
	Total Output	Items Produced	Employment (Contract)	Employment (Permanent)
Daily Average Temperature (°C)	-0.0768*	-0.0504***	-0.135***	0.00386
	(0.0449)	(0.0162)	(0.0472)	(0.0319)
Temperature × Neutral	0.0192	0.0205	0.00460	-0.00509
	(0.0590)	(0.0276)	(0.0661)	(0.0468)
Temperature × Flexible	0.0888	0.0380	0.125	0.0566
	(0.0647)	(0.0264)	(0.0785)	(0.0414)
Rainfall Controls	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends			
Observations	36,985	36,985	18,712	35,818

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Panel A presents the results from regression the outcome variable on the level of temperature and monsoon rainfall. Panel B presents the differential effects of temperature across labor regulation environments. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table E12: Alternative Measures of the Labor Regulation Environment – (Neutral and Flexible Binary Variables)

	log Wages and Productivity				
	Avg. Day Wage (Contract)	Avg. Day Wage (Permanent)	Output per Worker	TFPR	TFPR (CES)
Daily Average Temperature (°C)	0.000705	-0.0731***	-0.0755*	-0.0807***	-0.0844***
	(0.0263)	(0.0169)	(0.0415)	(0.0250)	(0.0260)
Temperature × Neutral	0.0345	0.0247	0.00638	0.0231	0.0297
	(0.0337)	(0.0234)	(0.0525)	(0.0265)	(0.0266)
Temperature × Flexible	-0.0736*	0.0493*	0.0655	0.0459	0.0440
	(0.0383)	(0.0278)	(0.0625)	(0.0333)	(0.0336)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends				
Observations	18,712	35,818	36,985	33,440	33,464

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Panel A presents the results from regression the outcome variable on the level of temperature and monsoon rainfall. Panel B presents the differential effects of temperature across labor regulation environments. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table E13: Alternative Measures of the Labor Regulation Environment – (Flexible and Neutral Combined Binary Measure)

	log Output and Employment			
	Total Output	Items Produced	Employment (Contract)	Employment (Permanent)
Daily Average Temperature (°C)	-0.00281	-0.0131	-0.0380	0.0429*
	(0.0351)	(0.0114)	(0.0336)	(0.0232)
Temperature × Flexibility	0.0487	0.0217*	0.0705*	0.0299
	(0.0324)	(0.0130)	(0.0383)	(0.0203)
Rainfall Controls	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends			
Observations	36,985	36,985	18,712	35,818

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Panel A presents the results from regression the outcome variable on the level of temperature and monsoon rainfall. Panel B presents the differential effects of temperature across labor regulation environments. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table E14: Alternative Measures of the Labor Regulation Environment – (Flexible and Neutral Combined Binary Measure)

	log Wages and Productivity				
	Avg. Day Wage (Contract)	Avg. Day Wage (Permanent)	Output per Worker	TFPR	TFPR (CES)
Daily Average Temperature (°C)	-0.0373**	-0.0256**	-0.0246	-0.0372**	-0.0394**
	(0.0160)	(0.0113)	(0.0310)	(0.0179)	(0.0184)
Temperature × Flexibility	-0.0371*	0.0280**	0.0354	0.0260	0.0254
	(0.0191)	(0.0141)	(0.0311)	(0.0167)	(0.0169)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends				
Observations	18,712	35,818	36,985	33,440	33,464

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Panel A presents the results from regression the outcome variable on the level of temperature and monsoon rainfall. Panel B presents the differential effects of temperature across labor regulation environments. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

E.4 Concerns Relating to the Endogenous Selection of Firms around the Regulatory Threshold

One concern relates to the endogenous selection of firms around the regulatory threshold. To mitigate these concerns I run the baseline specification dropping firms that have employment within 20% of the thresholds.

Table E15: Baseline Specification - Dropping Firms with 20% of the Threshold

	log Output and Employment			
	Total Output	Items Produced	Employment (Contract)	Employment (Permanent)
Daily Average Temperature (°C)	-0.0933 (0.0572)	-0.0458* (0.0247)	-0.180** (0.0717)	0.0114 (0.0386)
Temperature × Flexibility	0.190** (0.0931)	0.0486 (0.0391)	0.254** (0.111)	0.0462 (0.0572)
Rainfall Controls	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends			
Observations	32,475	32,475	16,624	31,631

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Panel A presents the results from regression the outcome variable on the level of temperature and monsoon rainfall. Panel B presents the differential effects of temperature across labor regulation environments. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table E16: Baseline Specification - Dropping Firms with 20% of the Threshold

	log Wages and Productivity				
	Avg. Day Wage (Contract)	Avg. Day Wage (Permanent)	Output per Worker	TFPR	TFPR (CES)
Daily Average Temperature (°C)	0.0307 (0.0355)	-0.0777*** (0.0237)	-0.0865* (0.0523)	-0.0940*** (0.0293)	-0.0981*** (0.0310)
Temperature × Flexibility	-0.112** (0.0526)	0.0972*** (0.0370)	0.141 (0.0869)	0.101** (0.0431)	0.106** (0.0445)
Rainfall Controls	Yes	Yes	Yes	Yes	Yes
Fixed Effects	Sector × District, Sector × Year, and State-Year Time Trends				
Observations	16,624	31,631	32,475	29,489	29,510

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Panel A presents the results from regression the outcome variable on the level of temperature and monsoon rainfall. Panel B presents the differential effects of temperature across labor regulation environments. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table E17: Baseline Specification - Uniform Thresholds

	log Output and Employment			
	Total Output	Items Produced	Employment (Contract)	Employment (Permanent)
Panel A: Above 100 UP dropped				
Daily Average Temperature (°C)	-0.169***	-0.0467*	-0.144**	-0.0225
	(0.0582)	(0.0240)	(0.0692)	(0.0429)
Temperature × Flexibility	0.215**	0.0555	0.172	0.102*
	(0.0937)	(0.0365)	(0.108)	(0.0562)
Observations	35,102	35,102	17,716	33,980
Panel B: Above 120 UP dropped				
Daily Average Temperature (°C)	-0.114*	-0.0373	-0.145**	0.00615
	(0.0656)	(0.0278)	(0.0708)	(0.0492)
Temperature × Flexibility	0.183*	0.0362	0.197*	0.0478
	(0.104)	(0.0429)	(0.111)	(0.0693)
Observations	30,709	30,709	15,722	29,913
Panel C: Above 300				
Daily Average Temperature (°C)	-0.162*	-0.0511	-0.253**	-0.0566
	(0.0862)	(0.0349)	(0.101)	(0.0623)
Temperature × Flexibility	0.308**	0.0790	0.412***	0.171*
	(0.128)	(0.0532)	(0.151)	(0.0901)
Observations	14,264	14,264	8,144	14,048
Panel C: Above 360				
Daily Average Temperature (°C)	-0.160*	-0.0510	-0.194*	-0.0491
	(0.0892)	(0.0374)	(0.111)	(0.0723)
Temperature × Flexibility	0.260**	0.0932*	0.279*	0.151
	(0.131)	(0.0558)	(0.167)	(0.106)
Observations	11,491	11,491	6,592	11,333

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. UP dropped = Uttar Pradesh dropped. This is because the firm-size threshold for UP is 300. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

Table E18: Baseline Specification - Uniform Thresholds

	log Wages and Productivity				
	Avg. Day Wage (Contract)	Avg. Day Wage (Permanent)	Output per Worker	TFPR	TFPR (CES)
Panel A: Above 100 UP dropped					
Daily Average Temperature (°C)	0.0325	-0.0786***	-0.129**	-0.0888***	-0.0909***
	(0.0361)	(0.0217)	(0.0520)	(0.0323)	(0.0336)
Temperature × Flexibility	-0.125**	0.0800**	0.140	0.0802*	0.0800*
	(0.0537)	(0.0355)	(0.0854)	(0.0464)	(0.0471)
Observations	17,716	33,980	35,102	31,925	31,947
Panel B: Above 120 UP dropped					
Daily Average Temperature (°C)	0.0287	-0.0789***	-0.0826	-0.0897***	-0.0900***
	(0.0361)	(0.0217)	(0.0520)	(0.0323)	(0.0336)
Temperature × Flexibility	-0.116**	0.0941**	0.117	0.0849*	0.0839*
	(0.0555)	(0.0409)	(0.0930)	(0.0473)	(0.0486)
Observations	15,722	29,913	30,709	28,039	28,059
Panel C: Above 300					
Daily Average Temperature (°C)	0.0838*	-0.0533*	-0.0966	-0.0938***	-0.0798**
	(0.0473)	(0.0323)	(0.0870)	(0.0310)	(0.0326)
Temperature × Flexibility	-0.184***	0.0764	0.170	0.116**	0.0869*
	(0.0707)	(0.0477)	(0.121)	(0.0491)	(0.0517)
Observations	8,144	14,048	14,264	12,910	12,915
Panel D: Above 360					
Daily Average Temperature (°C)	0.0934*	-0.0611*	-0.144	-0.0710**	-0.0630*
	(0.0562)	(0.0362)	(0.0885)	(0.0348)	(0.0357)
Temperature × Flexibility	-0.178**	0.102*	0.204*	0.115**	0.0880
	(0.0833)	(0.0531)	(0.124)	(0.0517)	(0.0543)
Observations	6,592	11,333	11,491	10,423	10,428

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. UP dropped = Uttar Pradesh dropped. This is because the firm-size threshold for UP is 300. Standard errors are adjusted to reflect spatial dependence as modelled in Conley (1999) and serial correlation as modelled in Newey and West (1987). District distances are computed from district centroids. Results are robust to clustering standard errors at the State Level.

F Adjustment Costs and the Potential Gains from Reallocation

This appendix provides an upper bound estimate of the gains associated with removing any adjustment costs that impede the movement of casual workers into permanent manufacturing positions. As discussed wage gaps could also be explained by skill differences and so do not necessarily imply a misallocation of talent. Consequently, the lower bound associated with this exercise is zero.

F.1 Modelling the Potential Gains from Reallocation

To provide some insight into the potential gains from reallocation I introduce some economic structure to the data and explore quantitatively the impact of removing the distortion between casual manufacturing employment and permanent manufacturing employment – a naïve counterfactual in which it is assumed that all differences in wages are driven by misallocation.

To assess the potential gains from reallocation I compare a hypothetical output level in which labor is efficiently allocated across activities to observed output following a similar approach taken in other firm-level and sector-level studies of misallocation (Restuccia and Rogerson, 2008, Hsieh and Klenow, 2009, Vollrath, 2009, 2014, Gollin et al., 2014).

Assuming that each activity operates with a Cobb-Douglas production technology and maximises profits, the wage distortion τ can be identified from the first-order condition,

$$w_j = (1-\alpha)\Lambda_j L_j^{-\alpha}\left[\frac{1}{\tau}\right] \tag{19}$$

where $\Lambda_j = p_j A_j$. The presence of adjustment costs, τ, will distort the amount of labor used in activity j compared to the level used in the absence of the distortion. As τ falls labor becomes relatively cheaper for activity j, and so the amount of labor that is utilised rises. In this context misallocation arises as the marginal revenue product of labor is not equalised across activities. To identify aggregate output two additional assumption are required. First, I assume that labor is perfectly substitutable across activities, i.e., there is no activity specific human capital. This implies that the total amount of labor in the economy is simply $L = \sum_j L_j$.[35] The second assumption is that prices are exogenously fixed, consistent with a small open economy in which all activities produce output that can

[35] This assumption implies that the gains from reallocation are an upper bound of the upper bound; however, if one considers sector-specific human capital as a constraint to reallocation then relaxing this constraint is part of the problem.

be traded internationally.[36] Under these assumptions observed output in the economy with adjustment costs can be written,

$$Y = \left(\sum_j \Lambda_j^{1/\alpha} \left[\frac{1}{\tau}\right]^{1/\alpha}\right)^{\alpha} \left(\sum_j L_j\right)^{1-\alpha}$$

which follows from using equation 19 for each activity to solve simultaneously for the shares L_j/L, and then taking the sum of output across activities. In the presence of adjustment costs Y is below the output-maximising level. Consequently, one can estimate, given the structure imposed above, how much output would rise under the counterfactual in which these adjustment costs are removed. The counterfactual output after removing these adjustment costs is written,

$$Y^* = \left(\sum_j \Lambda_j^{1/\alpha}\right)^{\alpha} L_j^{1-\alpha}$$

With both observed output and counterfactual output levels, the gains from reallocation can be written as,

$$G = \frac{Y^*}{Y} = \frac{\left(\sum_j \Lambda_j^{1/\alpha}\right)^{\alpha}}{\left(\sum_j \frac{\Lambda_j^{1/\alpha}}{\tau^{1/\alpha}}\right)^{\alpha}}$$

providing a measure of the gains in aggregate productivity from eliminating the adjustment costs that impede the movement of labor across activities.

F.2 Estimating the Potential Gains from Reallocation

Given the model structure discussed above I estimate the gains from reallocation, $\hat{G}$, for each firm providing the average gains from reallocation, as well as the distribution of gains.

Under the naïve assumption that the only difference in wages across activities is driven by misallocation the average (observable) wage in the destination activity is,

$$\mathbb{E}[w_j] = \mathbb{E}[w_i]\tau,$$

In log-linear terms, the distortion can therefore be estimated as the log-difference in average wages across sectors,

[36] With endogenous prices the gains from reallocation would be smaller as an equivalent movement of workers out of casual activities raises the marginal revenue product of labor by more than if prices are held fixed.

$$\log \tau = \log \mathbb{E}[w_j] - \log \mathbb{E}[w_i]$$

Taking this to the data, I estimate the following moment for each firm,

$$\mathbb{E}[\tau] \quad = \quad \exp(\log \mathbb{E}[w_j] - \log \mathbb{E}[w_i])$$

In addition, I use estimates of the average permanent manufacturing wage, $\mathbb{E}[w_p]$, the average casual manufacturing wage, $\mathbb{E}[w_c]$, and the number of workers in each activity, L_j.

With these estimates, and an assigned value of α, I estimate output in each activity, Λ_j,

$$\hat{\Lambda}_j = \frac{\hat{w}_j \hat{\tau}}{1-\alpha} \hat{L}_j^{\alpha}$$

These values are then used to construct estimates for the observed level of output $\hat{Y}$, the counterfactual level of output $\hat{Y}^*$, and, with these estimates, the estimated gains from reallocation $\hat{G}$.

$$\hat{G} = \frac{\hat{Y}^*}{\hat{Y}} = \frac{\left(\sum_j \hat{\Lambda}_j^{1/\alpha}\right)^{\alpha}}{\left(\sum_j \frac{\hat{\Lambda}_j^{1/\alpha}}{\hat{\tau}^{1/\alpha}}\right)^{\alpha}}$$

F.3 Counterfactual Estimates

In considering the gains from reallocation I construct a counterfactual that removes the total wage gap across activities providing an upper bound on the size of adjustment costs. The results of this exercise are presented in table F1.

Table F1: The Average Output Gains from Reallocation

	(1)	(2)	(3)	(4)	(5)
Naïve Gains	1.196	1.131	1.089	1.062	1.043
Labor Share ($(1-\alpha)$)	0.9	0.8	0.7	0.6	0.5

Notes: These estimate provide an upper bound of the static gains from reallocation under the assumption that the total wage gap between casual manufacturing workers and permanent manufacturing workers are driven by adjustment costs. The lower bound estimate of the static gains from reallocation are therefore zero.

I estimate that the removal of adjustment costs τ_j would result in an 8.9% increase

in the manufacturing output of regulated firms hiring both casual and permanent workers ($\alpha = 0.3$), a non-trivial increase.

As emphasised, it is beyond the scope of this exercise to provide inferences about the relative contribution that adjustment costs may play in explaining the wage gap between casual and permanent manufacturing workers. Instead this exercise provides an upper bound on the gains from reallocation, under the assumption that the total wage gap is driven by adjustment costs. The lower bound is zero. Understanding the relative importance that adjustment costs play in impeding the movement of workers out of casual employment and into permanent positions remains an important area for future research.