Agricultural Productivity, Factor Reallocation, and Industrial Production in the Short Run: Evidence from India[1]

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Abstract

This paper examines whether short-run changes in agricultural productivity results in factor reallocation into and out of the manufacturing sector, and whether adjustment costs impede this process, resulting in misallocation. Drawing on the results from a simple theoretical framework, I combine worker, firm, and district-level data with high-resolution data on atmospheric parameters to examine the effects of weather - a strong driver of short-run agricultural productivity - on industrial production and labour market outcomes in India. While temperature increases are shown to have a significant negative effect on agricultural yields ($-26.7\%/1°$C)*, wages* ($-7\%/1°$C)*, and employment* ($-5.7\%/1°$C) *the effect on manufacturing outcomes is ambiguous. By exploiting spatial variation in, and firm-level exposure to, India's labour regulation environment, I estimate the factor reallocation effect, net of the remaining channels. In rigid labour markets, with fewer employment opportunities, the production and employment of regulated firms contracts. However, in flexible labour market environments, we observe an expansion in production* ($9.81\%/1°$C) *and employment* ($11.4\%/1°$C)*, exploiting a decline in the cost of unskilled labour* ($4.9\%/1°$C)*, offsetting the contractionary effects of inclement weather. These results imply that factor reallocation could substantially offset economic losses in more "climate sensitive" sectors, highlighting the empirical relevance of general equilibrium effects, as well as the importance of economic diversification and integration in the management of localized productivity shocks.*

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1 Introduction

For many developing countries the importance of agriculture in terms of production and employment implies that changes in productivity should also affect other sectors of the economy through general equilibrium effects. However, most empirical analysis that explores or exploits changes in agricultural productivity usually assumes these general equilibrium effects to be small or non-existent. This paper aims to understand the empirical relevance of these general equilibrium effects by exploring whether whether short-run changes in agricultural productivity results in factor reallocation into and out of the manufacturing sector, and whether adjustment costs impede this process, resulting in misallocation.

I construct a simple theoretical framework that illustrates the general equilibrium effects of sector-specific productivity shocks, through local labour markets, in the presence of factor market distortions (section 3). The model indicates that a decline in agricultural productivity, shifting the relative productivities between sectors should result in a movement of labour from agriculture into the manufacturing sector, conditional on there being external demand for manufactured goods. However, with the presence of adjustment costs in the manufacturing sector, reallocation is impeded and misallocation occurs.

Drawing on the results from this framework, I combine worker, firm, and district-level data with high-resolution atmospheric parameters to examine the effects of weather - an important driver of short-run agricultural productivity - on industrial production and labour market outcomes in India between 2001 and 2007 (section 5). In order to understand the degree to which weather is a driver of factor reallocation between agriculture and manufacturing, several empirical stages, drawn from the theory, must be demonstrated. First, does weather affect agricultural production? Secondly, does weather affect agricultural wages and employment? Finally, does weather affect production and labour market outcomes in manufacturing markets through factor reallocation?

I begin by testing the hypothesis that weather is an important driver of short-run agricultural productivity. Consistent with a large body of literature that has explored this relationship in India, and elsewhere, I show that an increase in temperature has a significant negative effect on agricultural yields ($-26.7\%/1°C$); however, across multiple weather datasets, rainfall is shown to have little explanatory power once temperature is controlled for. I then test the hypothesis that a reduction in agricultural productivity transmits into a reduction in agricultural wages and employment - a necessary condition for factor reallocation to arise. I compute the average day wage for agricultural labour in each district and the district share of agricultural employment from nationally representative worker-level data to test this hypothesis. Consistent with the results on agricultural yields, I observe that an increase in temperature is associated with a reduction in agricultural wages ($-7.1\%/1°C$) and a reduction in the district share of agricultural employment by ($-5.74\%/1°C$). Once again changes in rainfall are shown to have no effect, consistent with the absence of explanatory power observed in the agriculture results.

The final stage of analysis - the focus of this paper - is more complicated and faces a number of empirical challenges. The use of weather data in empirical analysis is both a blessing and a curse. On the one hand, the realisation of weather is exogenous and so provides random variation in short-run agricultural productivity. On the other hand, empirical estimates of the effect of weather on economic outcomes are often lacking a clear, and consequently insightful, interpretation. For the estimates of inclement weather on manufacturing outcomes to be interpreted as the result of factor reallocation between agriculture and manufacturing, we require that these outcomes are not affected by weather in any other way, either directly or through alternative agricultural channels. This is an absurdly strong assumption as there are many potential channels through which weather could affect manufacturing, both through agriculture and directly. Changes in agricultural productivity could affect manufacturing outcomes in sectors that use agricultural products as inputs, and a reduction in agricultural income could reduce the consumption base for manufactured products with local demand (Rijkers and Soderbom, 2013). 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, physical, or cognitive ability of workers and managers, or through an increase in absenteeism due to avoidance behaviour (Mackworth, 1946; 1947; Kenrick and MacFarlane, 1986; Hsiang, 2010; Cachon et al., 2012; Dunne et al., 2013; Advharyu et al. 2014; Burgess et al., 2014; Sudarshan and Tewari, 2014; Heal and Park, 2014; Graff Zivin and Neidell, 2014; Graff Zivin et al. 2014). Heavy rainfall may affect workers' ability to get to work (Bandiera et al., 2013) or disrupt supply chains. 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 (Alcott et al., 2014; Ryan, 2014). 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 (Asher and Novosad, 2014).[2] The difficulty associated with interpreting empirical estimates of weather variation are highlighted by the results of this paper. Estimates of the net effect of temperature and rainfall on manufacturing outcomes are shown to be statistically insignificant. The question remains as to whether these estimates are true zeros or the net

[2]Under the assumption that labour is more sensitive to temperature increases than capital, firms may shift towards more capital intensive production resulting in capital deepening.

effect of competing channels.[3]

Given this ambiguity, it is very difficult to interpret the empirical estimates of weather variables in a meaningful way. Where empirically relevant channels move in the same direction, we fail to have an economic interpretation that can be used to aid the design of appropriate interventions to mitigate losses or exploit opportunities. Where multiple channels are competing, economic losses and opportunities may be missed entirely or substantially underestimated. To understand the empirical relevance of a single channel, an identification strategy is needed that *"switches off"* the channel of interest for a subsample of the data, such that the difference between the empirical estimate for these two samples backs out the sign and magnitude of the effect, net of the remaining, empirically relevant, channels.

By exploiting spatial variation in, and firm-level exposure to, India's labour regulation environment, I identify the effects of short-run factor reallocation on manufacturing production and labour market outcomes through its interaction with year-to-year changes in weather variation. By comparing the net effect of temperature on regulated firms in rigid labour market environments to regulated firms in flexible labour market environments, the sign and magnitude of the factor reallocation effect can be identified as the only mechanism that varies between these two groups. I estimate that an increase in temperature is associated with a factor reallocation effect that increases production (9.8%/1°C) and employment (11.4%/1°C), alongside a reduction in the average day wage (4.9%/1°C).[4] In rigid labour market environments, we observe a large reduction in production (−7.1%/1°C) and employment (−9%/1°C) with no change in the average day wage. This indicates that temperature affects manufacturing outcomes through multiple channels in addition to factor reallocation, as discussed above. These results are consistent with the theoretical prediction that a reduction in the equilibrium wage results in a reallocation of employment, and that adjustment costs impede this process. Additional evidence and robustness tests further support this claim.

An important consideration is the type of worker that shifts between the factory and the field. It is reasonable to suppose that there are fundamental differences between the agricultural workers that respond to a reduction in agricultural productivity and the permanent labour force working in the manufacturing sector – who, in all likelihood, do not. Empirically, the firm-level data allows us to distinguish between workers based on their contract type within the firm: temporary contract workers and permanent workers. Under the

[3]Due to the potential for multiple channels I refrain from the use of these weather variables as instrumental variables because the exclusion restriction is clearly violated.

[4]All results within manufacturing are conditional on the firm surviving year-to-year changes in the weather (intensive margin adjustment); however, firm entry and exit (extensive margin adjustment) in response to random year-to-year changes in the weather seems unlikely to be a first order consideration.

assumption that agricultural workers in search of seasonal employment in the manufacturing sector are hired as temporary workers this provides the opportunity to both test the credibility of the papers' narrative as well as improve our understanding of the relationship between unskilled and skilled workers in the manufacturing sector. Consequently, the effects of an influx of unskilled workers on the employment outcomes of the permanent workforce. This provides an estimate of the elasticity of substitution between the average contract workers and the average permanent worker in manufacturing. This requires the assumption that permanent manufacturing workers do not respond to short-run variation in the weather, i.e., we must believe that firms are hiring agricultural workers as temporary workers, rather than permanent workers, an assumption that is supported using worker-level data. This analysis also helps to understand whether increases in manufacturing production arise due to a simple scale effect, or through an increase in process efficiency.

I find suggestive evidence that an increase in the number of contract workers improves the productivity of permanent workers, as seen through a relative increase in the average wage of permanent workers, a complementarity in the production process. This is indicative that the increase in production associated with an exogenous increase in unskilled labour arises, at least in part, from improvements in process efficiency, as opposed to an increase in the scale of production.

The premise that contract workers and permanent workers could be complements is plausible as section 10 of the 1970 Contract Labour Act prohibits the use contract labour if the work *"... is done ordinarily through regular workmen in that establishment."* Consequently, it may be reasonable to think that by hiring contract workers, permanent workers are able to engage in their activities more productively. Furthermore, it is reasonable to assume that the average contract worker is less skilled than the average permanent worker. To the degree that casual workers in agriculture are less-skilled than the average contract worker (and are employed as casual workers, rather than permanent workers) an influx of these workers reduces the skill level of the average contract worker, reducing the substitutability between contract and permanent workers.[5]

To understand the timing of adjustment, I exploit within-year variation in the agricultural season. The results show that the production and employment effects, are driven by variation in temperature during the growing season. However, the wage effect for contract workers, arises at the harvest period, when agricultural productivity is realised. This is consistent with the behaviour of rural-urban migrants in many developing countries who search for seasonal

[5]Clearly, this argument is reversed if unskilled agricultural workers were employed as permanent workers as this would reduce the skill level of the average permanent worker increasing the substitutability between contract and permanent workers. Neither the data, anecdotal evidence, or simple intuition provide support for this position.

work during the pre-harvest lean period and return to rural areas for work at harvest time if there is work available, i.e., if a good agricultural productivity draw productivity is realised.

To provide supporting evidence for the premise that factor reallocation is driven by an increase in external demand for manufactured products, I examine the effects of weather on an additional dataset comprising district-level shares of total manufacturing and agricultural exports. I observe that, in districts with rigid labour market environments, an increase in temperature is associated with a reduction in manufacturing exports, relative to districts with flexible labour markets, supporting the narrative of a positive factor reallocation effect. The magnitude of these effects are similar to the empirical estimates at the firm-level.[6] For sectors dependent on local demand we might expect to see a decline in output due to a reduction in the total income and, consequently, the consumption base of the local economy (Soderbom and Rijkers, 2013). However, economic losses to sectors dependent on local demand are likely to be mitigated in areas with a greater share of production in tradable goods. While the competitive wage falls, the number of hours worked in areas with external demand increases compared to areas that serve only local demand, where both the wage and the demand for labour falls. Consequently, in diversified economies with production in tradable goods, the reduction in demand for labour is offset, mitigating in part reductions in demand for non-tradable sectors. This emphasises the importance of economic diversification and integration in mitigating idiosyncratic productivity shocks (Autor et al., 2013; Costinot et al. 2012; Foster and Rosenzweig, 2004; Hornbeck and Keskin, 2012; Jayachandran, 2006; Mian and Sufi, 2012; Moretti, 2011).

Finally, I demonstrate that the results observed at the firm-level have economic significance at the aggregate level. Using district-level GDP for the combined manufacturing sector, I estimate a factor reallocation effect consistent in sign and magnitude to estimates at the firm level within the manufacturing sector. The interaction effect is insignificant for other unregulated sectors, such as agriculture, services, and construction. This provides further support for the identification strategy, namely that the estimated results are driven by the labour regulation environment, rather than other confounding factors.

Collectively, these results robustly support the premise that a short-run decline in agricultural productivity results in employment adjustment from farm to factory. In addition, the results highlight the economic losses associated with adjustment costs, provide suggestive evidence the expansion of production arises from improvements in process efficiency

[6]We assume that either the agricultural products are tradable, or subsistence constraints are non-binding. The first assumption appears to be a better representation of India due to the Public Distribution System and the integration of Indian agriculture in global markets. In the case of a small open economy, subsistence constraints are non-binding as long as production in the global economy is enough to meet the constraint, i.e., production and consumption is separable.

rather than a simple scale effect, and call attention to the empirical challenges associated with the use of atmospheric data in econometric analysis. Most importantly, the results indicate the importance of analysing localized productivity shocks in a general equilibrium framework, reducing the risk of introducing substantial bias to empirical estimates by under- or over-estimating economic losses and/or opportunities.

The remainder of the paper is structured as follows: section 2 presents a brief review of the literature and provides the context of the study; section 3 presents the theoretical framework; section 4 presents the empirical strategy and data; section 5 presents the empirical results and supporting evidence; section 6 discusses policy implications and conclusions.

2 Literature Review

This section provides a brief literature review grounding the focus of this paper within a broader set of research themes that have previously been studied.

This paper contributes to several strands of literature. The broad focus is in understanding the degree to which idiosyncratic productivity shocks can have economic consequences for sectors of the economy that are not directly affected. This relates to a literature exploring the origins of aggregate fluctuations, observing that economy-wide shocks have little explanatory power in explaining business cycle fluctuations (Cochrane, 1994). This has led economists to explore the role that idiosyncratic shocks play in explaining aggregate fluctuations. The idea that idiosyncratic shocks could explain aggregate fluctuations has for a long time been discarded due to a "diversification argument" (Lucas, 1977; Javanovic, 1987). It is observed that aggregate output concentrates around its mean at a very rapid rate; consequently, microeconomic shocks should average out and only have negligible aggregate effects. However, in recent years a number of papers have falsified this argument. Acemoglu et al., (2012) make the point that the diversification argument ignores the presence of interconnections between firms and sectors, which may propogate shocks throughout the economy. This idea is founded on a rapidly expanding literature that explores the role that networks play in economic activity (Jackson, 2010; Atalay et al., 2012, Carvalho and Gabaix, 2013). Gabaix (2011) also shows that the diversification argument can be rejected when the firm-size distribution is sufficiently heavy-tailed, i.e. idiosyncratic shocks to large firms or sectors have the potential to generate nontrivial aggregate fluctuations that affect total GDP, and via general equilibrium, all firms/sectors. Given the importance of agriculture in terms of employment and production for many developing countries, it is plausible that agricultural productivity shocks may have far reaching effects throughout the economy. However, there is very little empirical evidence to support this premise. I explore the degree to which agricultural productivity shocks can propagate through local labour markets impacting other sectors of the economy. As discussed above, the flexibility of agricultural workers alongside the spread of manufacturing towards rural areas in India provides a unique opportunity to identify the presence of such effects.

This relates to a literature that examines the role that factor reallocation can play in mitigating the economic consequences of productivity shocks (Feng, Oppenheimer, and Schlenker, 2012; Gray and Mueller, 2012; Mueller, Gray, and Kosec (2014); Hornbeck, 2012; Jayachandran, 2006) and the role that mobility and adjustment costs play in impeding this factor reallocation. Adjustment costs are known to be a determining factor in governing responses to productivity shocks (Oi, 1962; Nickell, 1978; Bentolila and Bertola, 1990; Hopenhayn and Rogerson, 1993; Caballero et al., 1997; Besley and Burgess, 2004; Heckman and Pages, 2003; Haltiwanger et al. 2008; Ahsan and Pagés, 2009; Artuc et al., 2010; Dix-Carneiro, 2011; Notowidigdo, 2011; Autor et al., 2013; Advahryu et al., 2013; Bryan et al., 2013; Morten, 2013; Morten and Oliviera, 2014; Artuc et al., 2014; Gollin et al. 2014). Higher adjustment costs reduce the present discounted value of ex ante wages, especially in sectors (regions) exposed to a higher variance of productivity shocks. This paper argues that hiring and firing costs reduce the extent to which factor reallocation can mitigate the economic consequences of inclement weather: during a good agricultural season, firing costs reduce the number of layoffs; during a bad agricultural season, hiring is curbed due to the possibility of having to layoff workers in the future. A further question is the degree to which micro distortions affect aggregate outcomes (Banerjee and Duflo, 2005; Rogerson and Restuccia, 2008; Hsieh and Klenow, 2009; Kaboski and Townshend, 2012; Udry, 2012; Peters, 2013; Gollin et al., 2014). By examining the effects of the labour regulation environment using both firm-level and district-level GDP, we can examine the consistency of the results from both a microeconomic and macroeconomic perspective.

Within this literature the importance of economic diversification and integration in mitigating productivity shocks has been repeatedly emphasised (Foster and Rosenzweig, 2004; Jayachandran, 2006; Burgess and Donaldson, 2010; Moretti, 2011; Costinot et al. 2012; Hornbeck and Keskin, 2012; Mian and Sufi, 2012; Bryan et al., 2013; Autor et al., 2013; Donaldson, forthcoming). The sign of any general equilibrium effect depends on the degree to which local markets are integrated in a larger market either nationally or global. For there to be the potential for factor reallocation towards industry, it is necessary that the market extends beyond the exposure of any negative agricultural productivity shock. This is because a reduction in productivity reduces the total income in the economy and consequently the consumption base.[7] If there is no source of external demand for, or supply of,

[7]This is further exacerbated where subsistence constraints are binding.

products with subsistence constraints, then this will reduce the demand for industrial products locally resulting in contractionary general equilibrium effects. This consideration is of great importance when examining the role that income diversification can play in smoothing consumption, and has largely been ignored by the literature to date where data limitations have only been able to demonstrate adjustments in activity on the extensive margin without understanding the welfare consequences of such adjustments. One can imagine households diversifying into micro-enterprises, spending their time engaging in these activities with very low economic returns. Consequently, having a diversified economy that is integrated in a wider market is necessary if market responses are to mitigate aggregate welfare losses.[8]

Finally, I contribute to a rapidly expanding literature that aims to understand climatic influence on economic outcomes. The relationship between natural and economic systems has been a widely debated area of interest in academic and policy circles dating back to the time of Aristotle (384–322 BC), Montesquieu (1689–1755), and Buckle (1821–1862), with central importance for environmental and development policy. More recently, arising from concerns surrounding climate change, this research agenda has reemerged to better understand climatic influence on economic and social outcomes (see Dell, Jones, and Olken (forthcoming) for a recent review of the literature).

While the relationship between environmental conditions and economic outcomes has been, and continues to be, widely debated (Arrow et al., 2004; Acemoglu et al. 2002; Auffhammer et al., 2006; Barro and Sala-i-Martin, 2003; Daly, 1996; Dasgupta, 2008; Easterly and Levine, 2003; Gallup et al. 1999; Miguel et al. 2004; Miguel et al. 2013) it is central to evaluating the costs and benefits of environmental and development policies, such as the regulation and mitigation of greenhouse gas emissions and investments in adaptation (Fankhauser, 1995; Mendelsohn et al. 2006; Nordhaus, 2008; Pindyck, 2013; Stern, 2007; 2013; Tol, 2002; 2009; Weitzman, 2013). However, our ability to estimate the impact that economic activity has on environmental systems is much better than our ability to explain the effect that the environment has on economic activity, which when considered from a public finance perspective can result in significant asymmetries in our understanding of the costs and benefits of intervention, p:

$$\max V(p) = max \left[\sum_i B_i(p) - \sum_j C_j(p) \right] \tag{1}$$

$\sum_j C_j$ is usually well characterised, however, our limited understanding of how environ-

[8]It is of course still important to take into consideration these general equilibrium effects within markets where these conditions do not hold. For example, we may imagine that in a local economy the effects of agricultural shock will be underestimated if we do not account for reductions in demand for non-tradable products.

mental factors impact economic outcomes implies that $\sum_i B_i$ is more likely to be underestimated. This results in an omitted variable bias and consequent undervaluation of the benefits of intervention, p. While there have been significant advances in the statistical and econometric tools available to evaluate counterfactual outcomes, and identify causal effects, these alone are not sufficient to fully understand climatic influence on economic outcomes, unless the relevant environmental parameters are accessible. This ultimately comes down to an issue of measurement. The complexities and correlations associated with climatological phenomena make it incredibly difficult to parameterise and identify the components that are most relevant for the economic and social outcomes under study. However, advances in both computer science and climatology have considerably increased both the access and quality of data products to aid in this fundamental challenge, resulting in a recent boom of studies that have aimed to address these important questions (see Auffhammer et al. (2013) for more details on how these developments can be exploited by economists).

This literature has explored an increasing number of outcomes including conflict (Burke et al. 2013; Hsiang et al. 2011; Fenske and Kala, 2012), health and education (Deschenes and Greenstone, 2011; Kudumatsu, 2011; Deschenes, 2012; Antilla-Hughes and Hsiang, 2013; Barecca et al. 2013; Burgess et al. 2014; Colmer, 2013; Graff Zivin and Neidell, 2013), labour productivity (Mackworth, 1946; 1947; Kenrick and MacFarlane, 1986; Hsiang, 2010; Dunne, Stouffer, and John, 2013; Advharyu et al. 2014; Sudarshan and Tewari, 2014; Heal and Park, 2014; Graff Zivin and Neidell, 2014; Graff Zivin et al. 2014), and other broader economic outcomes such as GDP and trade (Dell, Jones, and Olken, 2009; 2012; Costinot et al., 2012; Rossi-Hansberg and Desmut, 2012). In addition, there is a large body of theoretical and empirical research examining how agriculture is affected by environmental change (Deschênes & Greenstone, 2007; Guiteras, 2009; Schlenker & Roberts, 2009; Schlenker & Lobell, 2010; Burke and Emerick, 2013, Massetti et al. 2013). As a result over time we are improving our estimates of $\sum_i B_i$.

However, on the whole these papers present very little insight into the channels and mechanisms through which inclement weather can affect economic outcomes. While, this matters little for efforts focussed on understanding the physiological relationship between inclement weather and agriculture, where the channels are grounded in the natural sciences, it is a major issue when focussing on outcomes that have a greater potential to be affected through multiple socio-economic channels. Any estimate of the elasticity between weather and these outcomes will provide the net effect of all the competing and complementary channels. While identifying that effects exist is important for reducing the asymmetry between our understanding of the costs and benefits of environmental and development policies, it is not until we understand the mechanisms through which these effects occur that we can effectively design policies to address these impacts in the most cost-effective way. Furthermore, as this paper demonstrates, by failing to disentangle the separate channels, we may underestimate the magnitude of, or even fail to observe, large economic effects exacerbating the asymmetry between our understanding of the costs and benefits of policy interventions.

The objective of economic research on climate change should be to understand the potential channels through which climate change could have an effect so that policy can be designed and constraints relaxed such that individuals and firms can mitigate their exposure to present and future impacts. Furthermore, by refocussing the objective of research in this field towards understanding mechanisms we avoid the need to extrapolate empirical estimates based on weather variation towards the impacts of climate change, and consequently avoid the need to make assumptions about the endogenous response of current and future generations to climate change.

3 Theoretical Framework

In this section I present a simple general equilibrium model to illustrate the effects of localized productivity shocks on factor reallocation between sectors in the presence of adjustment costs. I consider a small open economy where there are two sectors, agriculture and manufacturing, and two factors of production, unskilled and skilled labour. I begin by describing the competitive benchmark, before introducing an extension in which adjustment costs affect the labour supply decision of workers.

3.1 Model Environment

Consider a small open economy, with a large number of unskilled and skilled workers, each of whom endowed with L units of unskilled labour and S units of skilled labour respectively. There are two sectors, manufacturing and agriculture, both of which are tradable. As both sectors are tradable consumption and production are separable. This eliminates the need to take a stand on preferences.

Production in the agricultural sector requires labour such that,

$$Q_a = A_a L_a \tag{2}$$

where Q_a denotes production in the agricultural sector, L_a the labour allocated to agriculture, and A_a labour productivity.

Production in the manufacturing sector requires both skilled and unskilled labour, taking the CES form:

$$Q_m = A_m \left[\gamma (A_L L_m)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_S S_m)^{\frac{\sigma-1}{\sigma}} \right]^{\frac{\sigma}{\sigma-1}} \tag{3}$$

where Q_m denotes production in the manufacturing sector, L_m the allocation of unskilled labour to the manufacturing sector, S_m the fixed stock of skilled labour in the open economy, A_m the hicks-neutral technical change parameter, A_L the unskilled labour-augmenting technical change parameter, and A_S the skilled labour-augmenting technical change parameter. The parameter $\gamma \in (0, 1)$ captures the share of each factor, and $\sigma > 0$, the elasticity of substitution between skilled and unskilled labour.

The production function in equation (3) implies the following ratio of the marginal product of skilled labour to the marginal product of unskilled labour,

$$\frac{MPS_m}{MPL_m} = \frac{(1-\gamma)}{\gamma} \left(\frac{A_S}{A_L} \right)^{\frac{\sigma-1}{\sigma}} \left(\frac{S_m}{L_m} \right)^{-\frac{1}{\sigma}} \tag{4}$$

Consequently, if skilled and unskilled labour are complements in production ($\sigma < 1$), an increase in the employment of unskilled labour will raise the marginal product of skilled labour relative to unskilled labour, ceteris paribus.

3.2 Competitive Equilibrium

In a small open economy that trades with the rest of the world prices are exogenously determined. The relative price of the agricultural sector is,

$$\frac{P_a}{P_m} = \left(\frac{P_a}{P_m} \right)^* \tag{5}$$

Profit maximisation implies that there must be factor price equalisation in each sector,

$$P_a MPL_a = w_L = P_m MPL_m \tag{6}$$

This implies that, in equilibrium, the marginal product of unskilled labour is determined by world prices and agricultural productivity.

$$MPL_m = \left(\frac{P_a}{P_m} \right)^* A_a \tag{7}$$

The equilibrium allocation of labour is determined by substituting the skilled labour clearing condition, $S_m = S$, into equation (7),

$$\gamma A_m \left(A_L L_m \right)^{-\frac{1}{\sigma}} \left[\Theta \right]^{\frac{1}{\sigma-1}} = \left(\frac{P_a}{P_m} \right)^* A_a \tag{8}$$

where $\Theta = \gamma(A_L L_m)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)(A_S S)^{\frac{\sigma-1}{\sigma}}$. Equation (8) implicitly defines the equilibrium level of unskilled labour in manufacturing, L_m^*, which based on the condition $L_m + L_a = L$, consequently determines the equilibrium level of unskilled labour in agriculture. Equilibrium production, can then be determined through equations (2) and (3).

3.3 The Transmission of Idiosyncratic Productivity Shocks Through Local Labour Markets

In this section we assess the response of employment shares in agriculture and manufacturing to idiosyncratic productivity shocks in the agricultural sector. We consider the effects of a change in agricultural productivity on the employment share of unskilled labour in manufacturing, as well as the marginal productivity of skilled labour.

A decrease in A_a generates a reallocation of unskilled labour from agriculture to manufacturing, i.e. $\frac{\partial L_a^*}{\partial A_a} > 0$ and $\frac{\partial L_m^*}{\partial A_a} < 0$. This arises from the fact that, in equilibrium, the marginal product of labour in the manufacturing sector is given by world prices, and agricultural productivity. A decrease in agricultural productivity reduces the marginal product of unskilled labour in agriculture because $\frac{\partial MPL_a}{\partial A_a} > 0$. Thus employment of unskilled labour in manufacturing must increase to reduce the marginal product of unskilled labour in manufacturing to the equilibrium level, because $\frac{\partial MPL_m}{\partial L_m} < 0$.

When unskilled and skilled labour are complements i.e., $\sigma < 1$, a reduction in agricultural productivity (A_a) will increase the marginal product of skilled labour. This is because an increase in the number of unskilled workers increases the ratio of marginal productivities between skilled and unskilled labour shown in equation (4). Given that the number of skilled workers is fixed, this will increase the wage of skilled workers.

In the event that unskilled and skilled labour are substitutes a reduction in agricultural productivity (A_a) will reduce the marginal product of skilled labour, due to a reduction in the ratio of marginal productivities between skilled and unskilled labour.

Reallocation in the Presence of Adjustment Costs

This section examines how the results in the competitive benchmark change if labour is unable to adjust without cost. At the heart of this extension is a non-arbitrage condition in which the worker is indifferent between working in Agriculture and Manufacturing. This condition implicitly derives the labour supply curve, determining the amount of reallocation that occurs in response to a labour demand shock. The inclusion of adjustment costs limits sectoral arbitrage and causes the incidence of productivity shocks to fall at least in part on the worker. This helps us to understand how employment shares in agriculture and manufacturing adjust to sectoral productivity shocks in the presence of adjustment costs.

Each individual begins the period as a worker in sector j. Workers can make an instantaneous decision about whether to remain in sector j or switch to an alternative sector, k. Indirect utility for a worker in sector j depends on their wage w_j.[9] The implicit labour supply curve is derived from the indirect utility function for the marginal unskilled worker in sector j, $v_j(w_j, \mathbf{p})$. Equilibrium requires that the marginal unskilled worker is indifferent between working in agriculture and manufacturing,

$$v_j(w_j, \mathbf{p}) = v_k(w_k, \mathbf{p}) \tag{9}$$

Labour is assumed to be supplied inelastically so that all variation in the sectoral allocation of workers comes from the reallocation decision. The cost to the marginal worker of switching from sector j to sector k is c_{jk}, where $c_{jk} > 0$ if $j \neq k$. In addition workers face an idiosyncratic moving cost, ε_{ijk}. All workers are identical except for their individual adjustment costs, ε_i and their initial sector.[10] The decision for worker i, in sector j, about which sector to work in is therefore the location with the highest utility,

$$\max_j \{v_j(w_j, \mathbf{p}) - \mathbb{1}_{j\neq k} c_{jk} - \varepsilon_{ijk}\}$$

In principal, the model can be solved for any distributional assumption for the idiosyncratic adjustment cost, ε_i; however, the model takes a particularly tractable form if we assume that the idiosyncratic adjustment costs are born from an i.i.d extreme-value type I distribution, as is standard in discrete choice models, with the cumulative distribution given by,

$$F(\varepsilon) = \exp(-\exp(-\varepsilon/\nu - \gamma))$$

where ν is a positive constant, the scale parameter, and $\gamma \cong 0.5772$ is Euler's constant. These Imply that $\mathbb{E}(\varepsilon_i) = 0$ and $Var(\varepsilon_i) = \frac{\pi^2\nu^2}{6}$ (See Patel, Kapadia, and Owen, 1976). Under this assumption we can derive the probability that a worker moves from sector j to sector k, conditional on them starting in sector j,

$$m^{jk} = \frac{\exp((\log w_k - \mathbb{1}_{j\neq k} c_{jk})\frac{1}{\nu})}{\sum_{j=1}^{N} \exp((\log w_n - \mathbb{1}_{j\neq k} c_{jn})\frac{1}{\nu})}, \quad \forall i \neq j$$

For workers that do not switch sectors, we calculate the probability that they stay in their current location, i.e. $\mathbb{1}_{j\neq k} c_{jk}) = 0$,

[9] This can be extended to include a sector specific utility effect, interpreted as the compensating differential across sectors.

[10] This assumption is unavoidable as we only have access to aggregate data. Dix-Carneiro (2014) introduces worker heterogeneity in a related structural model of labour mobility costs.

$$m^{jj} = \frac{\exp((\log w_k)\frac{1}{\nu})}{\sum_{j=1}^{N}\exp((\log w_n - \mathbb{1}_{j\neq k}c_{jn})\frac{1}{\nu})}$$

The total labour supply for sector k is determined by the net inflow of workers into each sector. Consequently, equilibrium labour supply in the presence of adjustment costs will depend on the initial distribution of workers across sectors. This is because the return to working in each sector is not the same for all workers: If there are many workers in sector j and it is not very costly to switch into sector k the inflow for workers to sector k will be larger than if there are fewer workers in sector j and it is more costly to switch sectors. As demonstrated in the competitive benchmark, the labour supply does not depend on the distribution of workers because the cost of switching sectors does not differ based on the initial sector - workers switch sector if sector k offers a higher level of utility, independent of their current job. If L_{jt-1} is the initial distribution of workers in sector j then the labour supply in sector j is the net inflow of workers into sector j from all other sectors (including those that start in sector j and decide not to switch sectors),

$$\begin{aligned} L_{jt} &= \sum_{k\neq j}^{N} m^{kj}L_{kt-1} + m^{jj}L_{jt-1} \\ &= \frac{\exp((\log w_k - \mathbb{1}_{j\neq k}c_{jk})\frac{1}{\nu})}{\sum_{j=1}^{N}\exp((\log w_n - \mathbb{1}_{j\neq k}c_{jn})\frac{1}{\nu})}L_{kt-1} + \frac{\exp((\log w_k)\frac{1}{\nu})}{\sum_{j=1}^{N}\exp((\log w_n - \mathbb{1}_{j\neq k}c_{jn})\frac{1}{\nu})}L_{jt-1} \end{aligned}$$

The new equilibrium is given by solving a system of simultaneous equations for gross labour flows between j and k (m^*_{jk}), the equilibrium allocation of labour (L^*_k), and the equilibrium wage (w^*_k), such that:

1) Labour demand is given by, $w_k = MPL_k$

2) The rate of sectoral reallocation is given by, $m^{jk} = \frac{\exp((\log w_k - \mathbb{1}_{j\neq k}c_{jk})\frac{1}{\nu})}{\sum_{j=1}^{N}\exp((\log w_n - \mathbb{1}_{j\neq k}c_{jn})\frac{1}{\nu})}$

3) Labour supply is given by, $L_{kt} = \sum_{k\neq j}^{N} m^{jkt}L_{jt-1} + m^{kk}L_{kt-1}$

This new sectoral equilibrium yield that the marginal worker is indifferent between staying in their current sector and switching to a different sector. In section 3.2, we demonstrated that when switching sectors was costless the marginal worker would receive the same wage in each sector; however, with costly adjustment, the marginal worker internalises the cost of switching sectors and only relocates if the wage received in the new sector is large enough to compensate for the cost of switching sectors. These adjustment costs result in a wedge between wages across sectors.

4 Empirical Specification and Data

In this section, I present the data and empirical strategy used to identify the factor reallocation effects of weather on industrial production.

4.1 Data

This main analysis of this paper combines data including (i) agricultural yields from the Directorate of Economics & Statistics Ministry of Agriculture, (ii) worker-level agricultural wage and employment data from the National Sample Survey (iii) plant-level data from the Annual Survey of Industries (ASI), (iv) daily weather data from the ERA-Interim Reanalysis data archive, and (v) a measure of the labour regulation environment based on data originally compilled by Besley and Burgess (2004) from state-level amendments to the 1954 Industrial Disputes Act.

The data is comprised of 316 districts in 24 states that have positive agricultural GDP, defined using 2001 district boundaries, observed between 2001 and 2007. In 2001, the average population of a district was 1.75 million people, and the average area was 5,462 km^2 (Census of India, 2001).[11] For the plant level data, I ensure the data is balanced along the district $\times$ year dimensions, i.e., there is at least one plant reported in each district $\times$ year cell. The data used in the agricultural and district level GDP analysis are balanced panels along crop $\times$ district $\times$ year and sector $\times$ district $\times$ year dimensions.

Manufacturing Data

Plant-level data comes from the Annual Survey of Industries (ASI), collected by the Ministry of Statistics and Program Implementation (MoSPI), Government of India. The ASI covers all registered industrial units, which include 10 or more workers and use electricity, or have at least 20 workers and do not use electricity. The ASI frame is divided into census, which is surveyed every year, and sample sectors, which are surveyed every few years. The census sample covers all firms the states of Manipur, Meghalaya, Nagaland, Tripura, and the Andaman and Nicobar Islands, and large factories. From 2001, the ASI defines large factors as those with 100 or more employees. In the sample survey, a third of all firms are randomly selected in the survey each year. The ASI has a much wider coverage than that of other datasets, such as the Census of Manufacturing Industries (CMI) and Sample Survey of Manufacturing Industries (SSMI). However, the ASI doesn't cover informal industry, outside of the Factories Act, 1948. The formal sector accounts for around two-thirds of manufacturing

[11]This is roughly twice the average area of a U.S. county (2,584 km^2), and nearly 18 times greater than the average population of a U.S. county (100,000).

output in India, and so is not representative of all manufacturing activities. However, it is representative of tradable manufacturing in India, as the informal sector likely trades very small volumes, if at all.[12]

The Dependent variables of interest are the log of total output, output per worker (a measure of productivity), employment, and the average day wage (defined as the average wage per worker/total number of days worked during the year). Employment outcomes are examined for both permanent workers and contract workers. Table 1 presents descriptive statistics for the sample. The sample selection is reported in table 2.

Agricultural Data

Data on crop yields is collected for each district and crop for the period 2001- 2007 from the Directorate of Economics & Statistics Ministry of Agriculture, Government of India. The crops are selected based on a decision rule that requires at least 1000 crop × district × year observation. This provides us with a balanced panel of crops that cover a minimum of 170 districts. The crops selected are: Arhar, Bajra, Barley, Gram, Groundnut, Jowar, Maize, Moong, Potato, Rapeseed & Mustard, Rice, Sesame, Sugarcane, Urad and wheat. I construct variable log yield – log(volume of crop produced/area cropped) – as the average for these 15 crops. Agricultural response functions are also estimated by crop (*forthcoming*)

Data on agricultural wages and employment comes from rounds 60, 61, 62, and 64 of the National Sample Survery, covering the period 2003 - 2007. This data consists of worker-level details on employment and remuneration allowing us to construct a measure of the agricultural wage that is more consistent with the market wage rate than alternative datasets such as the Agricultural Wages in India dataset that reports the equivalent wage of all workers. This approach is also consistent with other studies of rural labour markets in India that only use reported rural wage rates (Jayachandran, 2006; Kaur, 2014). Aggregating to the district-level provides details on the average day wage for agricultural workers, as well as the share of agricultural employment, defined as the total number of agricultural workers divided by the total number of workers in each district.

Weather Data

Atmospheric parameters 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 Temperature and Rainfall variables are constructed for each district centroid using

[12]Only the formal sector is regulated under the 1947 Industrial Disputes Act, an important attribute for identification when examining the role that the sectoral adjustment of labour plays in mitigating productivity losses.

inverse distance weighting from all grid points within 100km. The weight attributed to each grid point decreases quadratically with distance.[13]. Although, India has a large system of weather stations providing 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 since independence. Furthermore, there are many missing values in the publicly available series, resulting in a database with very few observations under a selection rule that requires data for 365 days of the year. Reanalysis data provides a solution to these issues, in addition to endogeneity concerns related to the placement of weather stations, as well as spatial variation in the quality of and the collection of data. By combining remote-sensing data with global climate models, a consistent best estimate of atmospheric parameters can be produced over time and space (Aufffhammer 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 data is increasingly being used by economists, especially in developing countries, where the quality and quantity of weather data is more limited (see Alem and Colmer, 2013; Burgess et al. 2014; Colmer, 2013; Guiteras, 2009; Hsiang et al. 2011; Kudumatsu, 2012; Schlenker and Lobell, 2010).[14]

The Labour Regulation Environment

The combination of these datasets provide the basis of the main empirical analysis. To identify of the existence of factor reallocation, net of the remaining channels, I exploit spatial variation in, and firm-level exposure to, the labour regulation environment of India. As discussed above, Industrial regulation in India has mainly been the result of central planning. The only exception to this is the area of industrial relations. This implies that the only spatial variation in policy that affects the manufacturing sector is related to the labour regulation environment. The key piece of legislation used to measure state-level variation in sectoral mobility, is the Industrial Disputes Act of 1947 (hereafter IDA). The IDA sets out conciliation, arbitration and adjudication procedures that are to be followed in the case of an industrial dispute and was designed to offer workers in the formal manufacturing sector some protection against exploitation by employers. Up until the mid 1990's the IDA was extensively amended at the state level result in in spatial variation in labour market rigidities.

[13]The results are robust to alternative methods of construction including: 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; the average of each point in the district weighted by population. These measures result in a smaller sample size as some districts do not contain a data point, requiring inverse distance weighting

[14]The results are robust to additional rainfall and temperature datasets from both satellite (TRMM) and ground station sources (Delaware).

Besley and Burgess (2004) use these extensive state-level amendments of the IDA (113 in total) to construct a measure of labour regulation 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 (0), pro-worker (+1), or pro-employer (-1). A pro-worker amendment is classified as one that decreases a firm's flexibility in the hiring and firing of workers, increasing hiring and firing costs. Pro-employer amendments are classified as increasing a firm's flexibility in hiring and firing. Neutral amendments are defined as having no effect on hiring and firing costs. In Besley and Burgess (2004) the cumulation of these scores for all previous years determines the state's labour market regime.

Given, the subjectivity of the assignment, there has been considerable academic debate on the classification of labour market regimes in India (Ahsan and Pages, 2009; Bhattacharjea, 2006; Gupta et al., 2008). In order to take these concerns into consideration I report results for a variety of adjustments to the Besley and Burgess (2004) coding. One example relates to the coding of Gujarat (pro-worker). Bhattacharjea (2006) notes that this classification is the result of one single amendment, allowing for "a penalty of 50 rupees a day on employers for not nominating representatives to firm level joint management councils." It is argued that this amendment is relatively inconsequential and so should be coded as neutral. Bhattacharjea (2006) focuses on state level differences to Chapter 5b of the IDA, requiring firms to seek government permission for layoffs, retrenchments, and closures.

Extending the approach taken by Besley and Burgess (2004), Bhattacharjea (2006) considers both the content of the amendments and judicial interpretations in his assessment of state labour regulation environments. Two types of regulatory changes are defined: those pertaining to the employment threshold beyond which permission for retrenchments, layoffs, or closures is required; and those to the requirement of obtaining permission for closure, or both closure and retrenchment. The first adjustment results in West Bengal being defined as the only Pro-Worker state. The second adjustment, based on permissions, identifies Maharashtra and Orissa as the states that have required permissions on more counts than other states over time.

I provide further support for the identification that these regulations provide through the construction of a more appropriate counterfactual environment. As the IDA is binding for firms with a number of workers above the thresholds of 50 in West Bengal, 300 in Uttar Pradesh, and 100 elsewhere, I restrict my analysis to all firms that above these thresholds. This allows us to compare the differential effect of temperature variation on production and employment outcomes between regulated firms in rigid states to regulated firms in flexible or neutral states. This also provides a test of the identification strategy by examining whether there are any effects of the regulation below the size thresholds.

For identification purposes, only pro-worker classifications should have any relevance for decision-making and so I group all other states as a comparison group.[15]

4.2 Empirical Strategy

The predictions of the theoretical model are examined empirically, by exploring the effects of rainfall and temperature within local labour markets. For the agricultural sector, the unit of observation, is a geographic area (district) in a given year. For the manufacturing sectors, the unit of observation is a manufacturing plant, in a geographic area (district) in a given year.

4.2.1 Main Specification

The main empirical specification for estimating the net elasticities of weather on the outcome variables is presented in the following model:

$$\ln\,(Y_{ijdt}) = f(w_{dt}) + \alpha_{jd} + \alpha_{jt} + \phi_s t + \varepsilon_{ijdt}. \tag{10}$$

The dependent variable, Y, for the agricultural sector is the natural log of yields, wages, or the district share of employment for district d at time t. For the manufacturing sectors the dependent variable, Y, is the natural log of total output, output per worker, contract worker and permanent worker employment, or the average daily manufacturing wage for contract and permanent workers for firm i, in sector j, of district d during year t.[16] $f(w_{dt})$ is a function of rainfall and temperature. Across all estimates, I restrict the data to only include regulated firms (defined using the size thresholds discussed above) and only estimate the effects in areas with a non-zero share of agricultural GDP.

Within-District industry (α_{jd}) fixed effects absorb all unobserved district $\times$ industry-specific time-invariant determinants of the dependent variables, given the repeated cross-section nature of the survey, this is as close to firm fixed effects as can be achieved. Industry $\times$ Year (α_{jt}) fixed effects control for sector-specific time-varying differences in the dependent variable that are common across districts. However, the assumption that shocks or time-varying factors that affect the outcome variables are common across all districts is unlikely to be valid. As a result, I also include a set of flexible state specific time trends. The

[15] When examining results using separate classifications for pro-employer and neutral the coefficients between these groups are not statistically different from each other. This is consistent with the identification strategy as the constraint relates to the incentive to hire. Neither neutral nor pro-employer states have any disincentive to hire workers in the short-run. Consequently, I group the two together for ease of interpretation.

[16] The average daily manufacturing wage is calculated as the total wage bill divided by the number of man days.

last term in equation 10 is the stochastic error term, ε_{ijdt}. Where it is computationally feasible I follow the approach of Hsiang (2010) by assuming that the error term ε_{ijdt} may be heteroskedastic and serially correlated within a district over time (Newey and West, 1987) and spatially correlated across contemporaneous districts (Conley, 1999; 2008). For each result I loop over all possible distances up to 1000km selecting the parameter value that maximises the standard errors. I then repeat this exercise for serial correlation. However, for the manufacturing regressions the dimensions of the data are too large to incorporate this approach. Consequently, 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 Conley (1999; 2008) standard errors. 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) rained agriculture in the United States.[17].

In the most basic specification $f(w_{dt})$ is modelled as a function of average daily temperature and total annual rainfall.[18] It is important to note that this paper does not use measures of rainfall or temperature as instrumental variables. These variables are not valid to be used as instruments as there are multiple channels through which they can affect outcomes, as this paper demonstrates, and consequently the exclusion restriction does not hold. Even if there was only one channel, the potential for non-linearities and consequently, heterogenous treatment effects makes these measures poor instrumental variables.

$$f(w_{dt}) = \beta_1(Temp_{dt}) + \beta_2(Rain_{dt}) \tag{11}$$

β_i is the net effect of each of the weather variables and measures the average elasticity of the outcome variable with respect to rainfall or temperature. In this respect β is a function of the factor reallocation effect (η) and the remaining empirically relevant channels (δ) i.e., $\beta_i = \delta + \eta$. Identifying the existence and relevance of η is the main empirical objective of the paper.

Atmospheric measures are defined annually starting at the end of the previous agricultural year in March, which also corresponds with the start of the new financial year. The main agricultural season, known as the Kharif season typically begins in June, and usually finishes

[17]Based on the regression results that account for spatial correlation using Conley standard errors, it appears that clustering at the state level is slightly more conservative, indicating that the standard errors on the manufacturing regressions may be too large

[18]When tested using Temperature and Rainfall Squared the effects on both Agriculture and Manufacturing are insignificant. This may be due to the relatively short length of the panel, indicating that temperature is locally linear during this period. Estimating the interaction terms between these variables and the labour regulation environment would have presented additional difficulties. Alternative measures used to capture non-linearities will be examined, discussed below.

harvesting by the end of November. The second lesser agricultural season, known as the Rabi season, typically begins around November and can go on until the following February. The Rabi season is dependent on the monsoon rains during the Kharif season for rainfall and generally produces crops that are more sensitive to higher temperatures, such as wheat. The months between March and May are broadly recognised as outside of the agricultural season – the lean season. In the main specification temperature is measured as the average daily temperature over the specified period. Additional specifications accounting for non-linearities in the temperature schedule are also explored. Rainfall is measured differently, to temperature as it is more able to be stored (in the soil, irrigation systems or tanks) than temperature. Consequently, rainfall is modelled as the sum of daily accumulations.

Identifying Factor Reallocation - Disentangling the Net Effect

Any estimate of the temperature and rainfall elasticities in equation 10 will be a net effect of the empirically relevant channels through which temperature affects manufacturing outcomes. In order to disentangle these effects, we exploit spatial variation in the labour regulation environment of India in combination with firm-level exposure to the regulation based on size thresholds. This approach not only captures variation in hiring and firing costs, but also identifies the channel through which economic spillovers arise, i.e., employment adjustment. The main concern for identification is the potential endogeneity of the labour regulation environment to manufacturing outcomes. However, the relevant identifying assumption is that the labour regulation environment is not endogenous to the previously existing relationship between temperature and manufacturing outcomes. As there is no relevant temporal variation in the labour regulation environment during the period of study, the level effect of the labour regulation environment on manufacturing outcomes is absorbed by the district fixed effects, and so is not identified. Consequently, even if the labour regulation environment is endogenous to manufacturing outcomes, it should not affect the identification of the effects considered.

There are a number of channels through which one could expect a rigid labour market environment to affect hiring and firing decisions. The most obvious channel is through an increase in the cost of labour, relative to other inputs. Such legislation, may also affect the firms ability to adjust labour in response to shocks, a rigidity effect, or through holdup problems, by which workers receive an increase in bargaining power, increasing labour costs and uncertainty about the appropriability of returns to investments.

We should expect that there would be less sectoral mobility in states with very strong pro-worker regulation environments (such as West Bengal). This is likely to be driven by a function of all the channels discussed, increasing hiring and firing costs. In this case we should expect less adjustment of labour into the manufacturing sectors in response to an increase in inclement weather. This may arise for a number of reasons. Most directly because short-run productivity shocks resulting from year-to-year variation in temperature provides less incentive for firms to hire workers, especially given the tendency for mean-reversion around average weather conditions. In this case, strong pro-worker legislation should mitigate the incentive that manufacturing firms have to make production adjustments in response to short-run demand shocks. In addition, regulated firms in pro-worker regions may engage in less labour-intensive forms of production resulting in fewer employment opportunities for unskilled labour. Associated with this argument, pro-worker legislation may affect workers' beliefs about the likelihood of employment. Bryan et al. (2014) demonstrate that ambiguity about the likelihood of gaining employment is a major deterrent for seasonal migrants, the workers we expect to most plausibly adjust in response to changes in agricultural productivity. Adjustment is not costless to workers and so seasonal workers may choose to migrate out of state, or into unregulated sectors – which ever is less costly – to mitigate the risk, and consequent loss, of not gaining employment. Whatever the driver, the absence of such adjustment implies that any residual variation captures the remaining net effect of the additional empirically relevant channels through which temperature could affect manufacturing outcomes.

I identify the sign and magnitude of the factor reallocation effect by incorporating an interaction between $f(w_{dt})$ and the labour regulation variable into equation 10.

$$\ln\,(Y_{idt}) = f(w_{dt}) + f(w_{dt}) \times \textsc{Pro-Worker}_d + \alpha_{jd} + \alpha_{jt} + \phi_s t + \varepsilon_{ijdt}. \tag{12}$$

where, $f(w_{dt})$ is a function of rainfall and temperature, and $f(w_{dt}) \times \textsc{Pro-Worker}$ is the interaction with states that have pro-worker labour regulation. The reference category is the interaction between rainfall and temperature with states that have a neutral labour regulation environment or a pro-employer labour regulation environment. The coefficient on the interaction term measures the inverse of the factor reallocate effect.

In order to provide greater support for the counterfactual, I exploit the size threshold for firms that are regulated by the IDA, dropping firms with fewer than 50 employees in West Bengal, 300 employees in Uttar Pradesh, and 100 employees elsewhere (Bhattacharjea, 2009). This results in a cleaner identification of the labour regulation effects. Firms with fewer employees are not directly affected by the regulation and so do not provide an appropriate counterfactual, introducing measurement error into the treatment definition. This also implies that other state-level characteristics that could confound the state-level variation of our treatment variable, such as whether these states are simply hotter (a heterogeneous treatment effect), or have greater access to irrigation (mitigating the economic consequences of inclement weather) would also have to differentially effect firms above the size threshold.

5 Empirical Results

This section presents the results from each of the empirical stages discussed above. First, we examine the effects of temperature and rainfall on agricultural yields, agricultural wages and the district share of agricultural employment. Following these results we examine the effects of temperature and rainfall on manufacturing outcomes. The results in section 5.1 and 5.2 follow the empirical specification from equation 10. The results in section 5.3 attempt to disentangle the factor reallocation effect from the remaining channels following the empirical specification in equation 12.

5.1 Agriculture - Yields, Wages, and Employment

In table 4 we examine the effects of temperature and rainfall on agricultural yields. Columns (1)-(3) present regression estimates of the effects of temperature and rainfall on the yield of all crops; Columns (4)-(6) present regression estimates of the effects of temperature and rainfall on the yield of kharif crops, the main growing season accounting for 65% of production; Columns (7)-(9) present regression estimates of the effects of temperature and rainfall on the yield of rabi crops, the secondary growing season accounting for 35% of production.

In panel A we observe that an increase in daily average temperature measured over the year is associated with a substantial decline in agricultural yields, whether they are grouped across all crops ($-19.6\%/1°C$), kharif crops ($-26.7\%/1°C$), or rabi crops ($-13.7\%/1°C$). In panel B, we observe that these declines are driven by increases in temperature during the growing season.

Across all estimates we observe that rainfall has very little explanatory power, especially once temperature is controlled for. This may be the result of the rapid increase in groundwater use during this period, reducing India's reliance on the monsoon rains. These results drive my focus on temperature as the socially relevant measure of weather for this analysis. An examination of the effects of rainfall on yields by crop and across crops results in significant coefficients. However, once temperature is controlled for these results become insignificant, with little variation in the estimates of temperature. The effect of rainfall on agricultural wages is insignificant irrespective of whether temperature is controlled for mitigating concerns about multicollinearity. This emphasises the importance of controlling for additional atmospheric variables when conducting economic analysis as the high correlations associated with atmospheric parameters results in the potential for large omitted variable biases. This is shown to be the case across specifications defined annually and seasonally.

In table 5, we observe the effects of rainfall and temperature on agricultural wages and the district share of employment in agriculture, based on data from the National Sample Survey between 2003 and 2007. A broader examination of the Indian labour market, alongside the activities of seasonal migrants is available in appendix B. This analysis demonstrates the importance of seasonal workers for labour markets in urban areas, also demonstrated by Imbert and Papp (2014).

We observe again that temperature is the main driver of any variation in these outcomes showing substantial declines in the agricultural wage ($-7.03\%/1°C$) and the district share of employment in agriculture ($-5.74\%/1°C$). Once again we observe that this variation is driven by the growing season as demonstrated in panel B. As with the results on agricultural yields, we observe that rainfall has an insignificant effect on agricultural wages or employment.

The absence of a rainfall effect may seem surprising; however, our priors on the importance of rainfall are based on a history of econometric estimates that fail to control for other atmospheric controls, namely temperature. Further evidence is needed to understand the degree to which rainfall matters for Indian agriculture over a longer time-horizon, however, these results are robust across weather datasets.

Nevertheless, it is encouraging to note that consistent with these findings a number of more recent studies have emphasised the importance of temperature variation over rainfall as a driver of economic outcomes (Burgess et al., 2014; Gray and Mueller, 2012; Mueller, Gray, and Kosec, 2014). In Pakistan temperature is shown to be a significant driver of migration in Pakistan, but rainfall is shown to have little explanatory power, providing further support for the results presented here.

Combined, these results indicate the importance of temperature as a driver of short-run agricultural productivity in India.

5.2 Manufacturing Outcomes - The Net Effect

Our analysis of manufacturing outcomes begins with an examination of the effects of daily average temperature and rainfall on the manufacturing outcomes discussed, following the approach taken by the previous literature estimating the net effect of the channels through which temperature and rainfall affects economic outcomes.

In table 6 we observe that temperature and rainfall have no statistical or economically significant effect on any of the outcome variables. This result is consistent across temperature specifications. These results are consistent with the findings of Burgess et al. (2013) who examine the effect of temperature on manufacturing output at the state level, and Hsiang (2010) who examines the effect of temperature on many sectors in the Caribbean, finding an insignificant, but positive effect on manufacturing GDP. However, it is important to understand whether this is a true zero effect or a net zero effect. In the absence of additional effects the question of why there is so little factor reallocation becomes important, indicating the presence of substantial adjustment costs. Alternatively, if it is the case that temperature affects manufacturing in ways that offset the factor reallocation effect, then by implementing policies to address these capricious effects manufacturing should see a net positive effect in response to an increase in temperature. In some cases, there appears to be double dividends to investing in energy efficiency schemes. Advharyhu, Kala, and Nyashadham (2014) find that the adoption of energy-saving LED lighting in Indian textile firms attenuates the effects of temperature on productivity by up to 75% in Indian textile factories using daily production data, indicating large co-benefits from the adoption of certain energy-saving technologies as well as a clear indication of the productivity effects that temperature can have. By using daily production data this paper provides the most compelling evidence that temperature has a direct effect on labour productivity.

5.3 Manufacturing Outcomes - Disentangling the Net Effect

To understand whether the estimated effects are true zero or a net effect of competing channels we implement the identification strategy discussed above, exploiting spatial variation in the Indian labour regulation environment combined with plant-level exposure to the regulatory effects. This approach results in differencing the net effects of temperature on regulated firms in rigid labour markets (switching off the reallocation channel) to regulated firms in flexible labour markets (where both channels remain). In the presence of additional temperature effects the interaction between temperature and the rigid labour market indicator will provide an estimate of these remaining channels ($\beta_1 Temp + \beta_2 Temp \times Pro - Worker$). Consequently, we can estimate the sign and magnitude of the factor reallocation elasticity as the inverse of the interaction term, the difference between the net effect in flexible labour markets ($\eta + \delta$) and the net effect in rigid labour markets (δ).

Tables 7 presents the results from the regression specification in equation 14 using the main assignment of the labour regulation environment used in the paper based on the adjustment to the Besley and Burgess (2004) index, reassigning Gujarat as a neutral state.

We begin by discussing the main results in table 7. Examining the effects on total output and labour productivity (output per worker), we observe that temperature has an expansionary factor reallocation effect (9.81%/1°C), net of the net effect of the remaining channels which is negative ($-7.1\%/1°C$). For temporary contract workers we observe a negative factor reallocation effect on the average day wage ($-4.9\%/1°C$), and an expansionary factor reallocation employment effect ($11.4\%/1°C$). The remaining net effect is negative ($-9.00\%/1°C$). Table 7 also shows that permanent workers experience an expansionary factor reallocation effect on the average day wage ($7.43\%/1°C$), however, there is no observed factor reallocation effect on employment - consistent with the idea that the employment of permanent workers does not adjust in response to weather variation. This is consistent with the notion that permanent workers and contract workers are complementary in production, i.e. an influx of unskilled labour improves the productivity of the average worker. This idea is supported by the 1970 Contract Labour Act, which in section 10 states that the use of contract labour is prohibited where the work *"... is done ordinarily through regular workmen in that establishment."* Consequently, it is plausible to consider that contract workers are hired into positions that better allow permanent workers to work more productively. Furthermore, it is reasonable to assume that the average contract worker is less skilled than the average permanent worker. To the degree that casual workers in agriculture are less-skilled than the average contract worker (and are employed as casual workers, rather than permanent workers) an influx of these workers reduces the skill level of the average contract worker, reducing the substitutability between contract and permanent workers. With this in mind the results presented are suggestive that the increase in production observed is driven, at least in part, by an increase in process efficiency, rather than a simple increase in the scale of production.

In support of the identification strategy, and consequent interpretation of the above results, table 8 presents the differential effects of temperature on the sample of manufacturing firms below the size threshold necessary for the IDA to have a binding effect. Across the labour market outcomes we observe no differential effect of temperature across labour regulation environments. This is not to say that there is no adjustment going on between agriculture and these smaller firms, but rather there is no variation that can be exploited to identify the factor reallocation effect. In fact, there is suggestive evidence that the net effect may be picking up a stronger factor reallocation effect than in the larger firms as we observe a positive increase in the average day wage of permanent workers, consistent with the hypothesis that an influx of unskilled agricultural workers may have positive effects on the productivity of the permanent manufacturing work force. We also observe that these small firms increase their output more in pro-worker states, which may be indicative of the impact that the rigid labour market environment has on the incentive for larger firms to hire these workers, reducing competition for the associated benefits of an increase in hiring. In addition, the magnitude of the employment coefficients, while insignificant, are not precisely zero, providing further support for this premise.

Table 9, presents alternative definitions of the labour regulation environment. Panel A assigns Maharashtra and Orissa as having rigid labour market environments, based on the states increased need to request permission to retrench workers or close facilities (Bhattacharjea, 2006). Panel B assigns West Bengal as having a rigid labour market environment based on the lower employment threshold needed before the regulation has a binding effect. Results across both alternative specifications are broadly consistent with the results in table 7. Panel C, includes an interaction term for Pro-Employer states demonstrating that the action observed in the data is driven by the rigidities associated with pro-worker states. Finally, panels D and E interact the pro-worker dummy with a continuous measure of labour market rigidities. The first measure that I construct is a measure of court efficiency. This aim to capture the degree of enforcement associated with the labour regulation environment. It is defined as the ratio of adjudicated cases in labour tribunals to total cases bought to labour tribunals within the state for the year 2000. In states where the share of resolved cases is higher it is reasonable to believe that this may capture a higher degree of enforcement in the labour regulation environment. The second measure used is the number of cases bought to labour tribunals per thousand workers within regulated industries. This measure aims to capture workers beliefs about the likelihood of enforcement. As we observe in table 9, both of these measures engender results that are consistent with an enforcement interpretation. As enforcement in pro-worker states increases, the magnitude of the remaining net effect increases indicating a lower rate of factor reallocation.

Combined, these results indicate the potential that factor reallocation effects can play in mitigating economic losses associated with temperature increases. By identifying the channels that constitute the remainder of the net effect, and designing effective interventions to address these effects, the factor reallocation effect could help to offset total losses associated with a decline in agricultural productivity.

These results demonstrate that general equilibrium effects flow through labour markets, consistent with the theoretical framework, and that firms with higher firing and hiring costs are less able to exploit changes in comparative advantage. Furthermore, this indicates that adjustments are short-run in nature and are not driven by structural change. If adjustments were permanent firms would not be affected by short-run variation in labour demand. If this were the case, there should be no differences in the coefficients between states that have pro-worker, neutral, or pro-employer labour regulation environments.

Furthermore, there is little reason to believe that random fluctuations in the weather should affect marginal workers to permanently switch sectors or permanently migrate. A negative direct effect in areas with high firing and hiring costs, further indicates evidence of a direct productivity effect, consistent with the narrative of the current literature (Advharyu et al. 2014). One limitation is the degree to which this effect can be further decomposed. We are unable to disentangle whether the reduction in output arises from workers having a reduction in labour productivity in the workplace, or whether physiological effects result in avoidance behaviour. While, it is interesting to try and understand these effects further, the policy implications in either case are likely to be the same. By improving the workplace environment, the physiological effects of temperature can be mitigated, either through increasing labour productivity or reducing avoidance behaviour, as shown in the United States (Graff Zivin and Neidell, 2014; Graff Zivin, Hsiang, and Neidell, 2013; Barrecca et al. 2013) and India (Advharyhu et al., 2014). The question of interest is why firms appear not to make use of air conditioning despite its wide availability. Whether the absence of air conditioning arises from fixed or variable cost constraints, a lack of effective electricity infrastructure, information constraints related to the effect of temperature on productivity itself, or other factors is the subject of future research. Advharyhu et al. (2014) indicate that information constraints appear to be a large factor, i.e. that firms are either unaware of the effects (an unknown unknown) or that they believe the effects to be small (an unknown known).

I find no statistically or economically significant effects associated with rainfall in the analysis of manufacturing outcomes. The effects of rainfall are thus interpreted to have no factor reallocation effect, consistent with the first-stage evidence on agricultural outcomes. While I still control for rainfall due to omitted variable bias concerns I do not report the coefficients for rainfall and focus instead on the economically interesting temperature effects.

Non-linearities in the Temperature schedule

A concern regarding the initial empirical specification, arises from the implicit assumption of linearity, regarding the effect of an increase in the daily average temperature. Economic losses are often modelled as independent of the initial temperature at a location and scale only with the magnitude of changes in average temperature (Stern, 2007; Tol, 2009; Dell et al., 2009; 2012). While the simplicity of this approach is appealing, recent studies have suggested that some impacts may depend strongly on the initial temperature of a location, and on non-linearities (Schlenker and Roberts, 2009; Burke and Emerick, 2013, Burgess et al. 2014; Deschênes and Greenstone, 2011; Graff Zivin and Neidell, 2014; Graff Zivin, Hsiang, and Neidell. 2013).

In identifying the effects of temperature on manufacturing we face a trade-off between the realism of the temperature schedule over the outcome variables and the power in which we can identify any effects that may be present. Power is a particular concern in the detection of general equilibrium effects and the presence of multiple channels makes accounting for non-linearities more difficult. This is further exacerbated by the lack of theoretical prior and robust evidence as to how the manufacturing sector responds over the temperature schedule. Consequently, it is important to think carefully about the underlying data-generating process. It is likely that the factor reallocation effect is the inverse of the agricultural response, which has previously been shown to be non-linear, i.e., losses are increasing and convex as temperature increases. However, decreasing returns to labour in manufacturing would indicate that the convexities associated with the agricultural mechanism may be offset by the concavity of the adjustment effect. A priori, it is unclear as to whether the factor reallocation effect itself is non-linear. Other effects of temperature on manufacturing may be more likely to be non-linear given the evidence on the physiological effects of temperature. Consequently, the degree to which the net temperature effects exhibit non-linearities depends upon the relative strength of the non-linearities in both the factor reallocation and remaining effects. If the concavity effects of the factor reallocation effects dominate the convexity of the agricultural response, then even if the remaining effects are convex, the estimated net effect may still be approximately linear.

I account for non-linearities in the temperature schedule in a number of ways. The first measure used is the cumulative degree days (CDD) approach. This measure captures the number of days that an outcome is exposed to temperature above a specified lower bound, with daily exposures summed over a period of time (e.g. annually, or seasonally). Denoting the lower bound as t_l, if t_d is the average temperature on a given day d, then CDD for the day are calculated as:

$$CDD_{d;t_l;t_h} = \begin{cases} 0 \text{ if } t_d \leq t_l \\ t_d - t_l \text{ if } t_l < t_d < t_h \\ t_h - t_l \text{ if } t_h \leq t_d \end{cases} \tag{13}$$

These daily CDD are then summed over the period of interest. 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 (Burgess et al. 2014; Burke and Emerick, 2014; Schlenker and Roberts, 2009). 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.

$$f(w_{dt}) = \beta_1 CDD_{dt;t_l;t_h} + \beta_2 CDD_{dt;t_h;\infty} + \beta_3 Rain_{dt} \tag{14}$$

$CDD_{dt;t_l;t_h}$ is the sum of the CDD between the bounds t_l and t_h. 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 $CDD_{dt;0;24} = \{0, 0, 8, 12, 24, 24\}$. 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 (annually or seasonally), 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.

Panel A, of table 10 presents the results from this piecewise linear function. In the estimation I set $t_l = 0$ and allow the data to determine t_h by looping over all possible thresholds and selecting the model with the lowest sum of squared residuals. I do this for the agricultural production function first to get the closest mapping to the agricultural response function. The selection for t_h also happens to correspond to the model with the lowest sum of squared residuals when estimating the manufacturing response functions. We observe that all of the action in the data is driven by temperatures in the higher temperature "piece" consistent with declines in agricultural productivity above these temperatures. Panel B, estimates the model again using only the higher temperature "piece" with little change in the estimated coefficients.

Finally, I construct an aridity index (UNEP, 1992) in an attempt to capture a measure that is more likely to capture the effects of inclement weather relevant for agriculture. This index is calculated by dividing rainfall by potential evapotranspiration. This captures the fact that moisture availability for plant growth is a function of evapotranspiration as well as precipitation. Following the lead of Henderson et al. (2014) I refer to this measure as a moisture availability index, because larger values indicate relatively greater water availability, with values above one indicating more moisture than would be evaporated given prevailing temperatures.

To construct the moisture availability index I construct a measure of Potential Evapotranspiration (PET) using the Thornwaite equation (1948). There are more accurate ways to calculate PET, however, they require extensive data on many more parameters than are available. As a consequence our measure of PET is likely subject to greater measurement error than more complex estimates. PET is calculated for each month using the following equation,

$$\text{PET}_m = 16\left(\frac{L}{12}\right)\left(\frac{N}{30}\right)\left(\frac{10 \times T_a}{HI}\right)^{\alpha}$$

Here T_a is the average daily temperature in degrees celcius, N is the number of days in the month being calculated, L is the average day length (hours) of the month being calculated, HI is a heat index $\sum_{i=1}^{12}\left(\frac{T_{ai}}{5}\right)^{1.5414}$, and $\alpha = (6.75 \times 10^{-7})HI^3 - (7.71 \times 10^{-5})HI^2 + (1.792 \times 10^{-2})HI + 0.49239$.

I calculate the average length of daylight in hours for each month, using the Forsythe et al. (1995) approximation,

$$\overline{\text{Daylight Hours}}_m = 24 - \left(\frac{24}{\pi}\right) \times \cos^{-1}\left(\frac{(\sin(\text{day type} \times \frac{\pi}{180}) + \sin(latitude) \times \sin(\phi_m))}{(\cos(latitude) \times \cos(\phi_m))}\right)$$

Where, $\pi = 3.14159$, latitude is measured in radians (latitude (°) $\times\frac{\pi}{180}$) and $\phi_m = \sin^{-1}(0.39795 \times \cos(0.2163108 + 2 \times \tan^{-1}(0.9671396 \times \tan(0.00860 \times (days_m - 186)))))$. Finally, the day type is set equal to 0.26667 based on the definition that sunrise/sunset is when the top of the sun is even with the horizon. The results are robust to alternative definitions defined by Forsythe et al. (1995). Together, these equations provide an estimate of the amount of evaporation that would occur if a sufficient water source were available. If we define actual evapotranspiration as the net result of the demand for moisture and the supply of moisture, then PET is a measure of the demand side.

The results in panel C are consistent with alternative definitions of weather, however, for most variables the results are not significant at conventional levels. However, it is important to note that the magnitude of the coefficients are large and economically significant indicating that measurement error in the construction of the PET index is likely to be driving this effect. Of interest we do observe a large significant factor reallocation effect on the employment of contract workers. A one percent reduction in moisture is associated with a 22% increase in the employment of contract workers through factor reallocation. In addition, we observe significant level effects on total output, output per worker, and the average day wage for contract workers in response to of a change in moisture. This is suggestive that the moisture availability index might be capturing directly a more isolated measure of the factor reallocation effect. In addition, while the interaction terms between the moisture index and rigid labour markets are insignificant, the combination of the level effect and interaction effect completely offsets the significant level effects observed consistent with the previous results.

Together, these results demonstrate the robustness of our findings to different specifications and functional forms, adding further credence to the interpretation of the effects.

Within-Year Variation: The Timing of Adjustment

In examining the seasonal effects of temperature, I begin by testing the premise that industrial production is affected by temperature through the impact of temperature on agriculture and that this channel drives any associated employment adjustment. To test whether this is plausible, I examine the impact of temperature and rainfall, both during the growing season, prior to harvest and during harvest.[19]

Hot weather during the pre-harvest period is known to limit the formation of grains, affecting the size of harvest. This reduces demand for labour, and wages during the harvest period, as demonstrated in table 5. This is also consistent with observations that seasonal migrants and workers usually work outside of agriculture during the lean-season prior to harvest, deciding whether to return for harvest upon the realisation of agricultural productivity.

The pre-harvest season is defined as the start of the lean or hungry-season in March through till the end of October, the end of the Kharif growing season. The harvest season, or post-hungry season is defined as November through till February incorporating the secondary rabi season.

Applying the identification strategy described in section 4.2, we are able to disentangle the direct effect from the indirect effect for each of the seasons to better understand the timing of adjustment. A priori it is plausible that adjustment is likely to occur during the lean-season as higher temperatures lower expectations about the returns to agriculture in the coming harvest season. As the season progresses, the returns to switching sectors will decline as fewer jobs will be available to workers who delay.

Table 11 presents the results of this analysis. Examining the effects of temperature on the total output, we observe very similar effects to those at the annual level for the factor reallocation effect (9.51%/1°C). This is driven by the growing season in support of our hypothesis. Similarly, for the results on labour productivity we observe significant effects driven by factor reallocation (6.01%/1°C) during the growing season and a smaller increase in labour productivity during the harvest period (2.62%/1$^\circ C$). The results on employment outcomes are also consistent with the results at the annual level; it appears that the reallocation effect for the contract workers occurs during the hungry-season, consistent with the premise that workers migrate during the lean season and return to work in agriculture upon the realisation of a bountiful harvest providing employment opportunities in agriculture. Migrants that wait until the realisation of the agricultural season are less likely to find work and may face difficulties in reaching employment opportunities due to effects of the monsoon

[19]Both the pre-harvest and harvest effects are estimated contemporaneously in order to address serial correlation within the year i.e. an increase in hot days during the pre-harvest season is likely to be correlated with an increase in hot days during the harvest season.

rains on transportation infrastructure if travel is required.

The Remaining Net Effect (*to be completed*)

While we are able to identify the factor reallocation effect, net of the remaining channels, the question remains as to what the remaining net effect may capture. This section should be treated as a preliminary diagnostic exercise providing some insight into which channels may be empirically relevant and in need of more detailed exploration and refined identification.

The results for this section are yet to be incorporated into the paper; however, I provide a brief summary of my findings so far,

- Using the product codes of the main inputs and imports (which, should have no effect as imports of agricultural products are unaffected by local productivity shocks) I identify agriculture linkage through production. Demand-side agricultural effects do not appear to have a contemporaneous contribution (need to look at lagged effect as this seems more plausible - but irrelevant for estimation of contemporaneous effects) - clear selection issues.

- Using information of the amount of electricity purchased from the grid and generated within-plant I show that an increase in access to electricity offsets a significant bulk of the negative effects consistent with the literature examining the physiological and contemporaneous effects of temperature on productivity - clear selection issues.

- I also look at the effects on capital depreciation. An increase in temperature has a level effect on capital depreciation - need to explore whether this is mitigated through electricity consumption. It's very difficult to think about how to interpret the effects on capital given the heterogeneity of capital. The age-old question, "what is capital?"

These results provide an indication of the relevant channels that contribute to the remaining net effect. I leave further study of these effects to future research in context that is better suited to identify the impact of these channels.

5.4 The Impact of Temperature on Exports - The Demand-Side

To further support the identification I examine the effects of temperature and its interaction with the labour regulation environment on manufacturing and agricultural exports. This helps to understand whether the observed effects are driven by external demand. I construct district-level trade flows by exploiting cross-sectional variation in each districts share of total manufacturing GDP (for manufacturing exports) and agricultural GDP (for agricultural exports) and multiplying it by the time-series variation in India-wide trade flows with each of its trading partners. This shift-share approach proxies each districts contribution to indian exports (Bartik, 1991), capturing local variation in each district's maximum contribution to the total value of exports and their interaction with national variation in trade over time. This approach implicitly assumes that the share of trade as a percentage of manufacturing GDP is constant, i.e., if manufacturing trade accounts for 20% of manufacturing GDP then district A that accounts for 10% of total manufacturing GDP is accorded a share of exports equal to 2% and district B with a share of total manufacturing GDP equal to 2% is accorded a share of total exports equal to 0.4%. Agricultural exports are defined as primary food products. Manufacturing exports are defined as total exports minus primary food products and transport related exports. This is to remove the share of exports that drive and support trade itself from the estimation. I estimate both equation 10 and 12, with the log of exports for each sector as the dependent variable.[20] I use district $\times$ trading partner fixed effects, year fixed effects and quadratic state $\times$ year time trends. To account for the substantial heterogeneity in exports between countries I estimate equations 10 and 12 by FGLS, weighting each district $\times$ trading partner time-series by the inverse variance of its residuals (Greene, 2003; Jones and Olken, 2010). Standard errors are clustered at the state level. Table 12 presents the results of this exercise.

We observe that an increase in temperature results in both a net reduction in manufacturing exports ($-2.17\%/1°C$) and agricultural Exports ($-3.37\%/1°C$). Applying the identification strategy used previously, I identify the sign and magnitude of the factor reallocation effect net of the remaining channels. We observe that the remaining channels account for a 13.6% reduction in manufacturing exports. The factor reallocation effect by contrast is associated with a 12.6% increase in manufacturing exports, similar in size to the previous estimates of temperature on production. In further support of the identifications strategy we observe no significant interaction effect between pro-worker labour regulation environments and temperature for agricultural exports.

6 The Macroeconomic Implications of Localized Productivity Shocks (*to be completed*)

This section aims to think about the total welfare effects of temperature on the Indian economy, through the use of district $\times$ sector GDP data. Given the aggregate nature of

[20]To account for the large number of zeros in exports to trading partners I use log(x+1).

the data the results are understandably less well identified. However, the consistency of the results is encouraging. Table 13 reports the results from examining the differential effect of the labour regulation environment on this new dataset.[21]

It is encouraging to see that the interaction term is only significant for the manufacturing sector, as this gives some credibility that the labour regulation environment is at least, in part being identified at the aggregate level.[22] The interaction should be insignificant for non-tradable sectors and agriculture, as these are not affected by the labour regulation environment conditions applied to the formal manufacturing sector. We observe significant negative temperature effects on total GDP ($-3.68\%/1°C$), Agriculture ($-14\%/1°C$), Tradable Services ($-2.11\%/1°C$), and Manufacturing ($-8.49\%/1°C$). Consistent with the results from the ASI, we observe a positive factor reallocation effect ($10.4\%/1°C$) for the Manufacturing sector. These results indicate the importance of localised productivity shocks on total economic output.

7 Conclusions

This paper explores the degree to which agricultural productivity shocks affect industrial production in the short-run through general equilibrium effects that propagate through local labour markets, or whether adjustment costs result in misallocation.

We observe, consistent with the theoretical predictions of a simple two-sector general equilibrium model, that short-run changes in agricultural productivity driven by year-to-year fluctuations in weather, namely temperature, reduces the demand for and return to labour in agriculture, resulting in an increase in the employment of unskilled labour in the manufacturing sector and a corresponding increase in production. This expansion of the unskilled labour force is associated with an increase in the productivity of the average permanent worker in the manufacturing manufacturing sector indicating that production increases are driven by improvement in process efficiency, rather than a simple scale effect. In addition to the identified factor reallocation effect, we observe that the remaining net effect is negative reducing production, labour productivity and employment. This results in a net zero effect overall.

These results highlight the role that market-responses can play in mitigating productivity losses, even across sectors. These effects are shown to be robust, both in terms of magnitude and statistical significance, to controlling for confounding explanations and hold across

[21] Given, the smaller number of observations the use of Conley (1999) standard errors is less computationally intensive. This error structure accounts for unknown forms of spatial correlation up to 500km.

[22] It is important to note that the identification is captured solely off of spatial variation in the labour regulation reducing the internal validity of the measure.

two additional datasets containing sector-specific district-level GDP data, and district-level shares of total manufacturing exports. This indicates the potential that casual labour in developing countries could actually be relatively responsive to changes in employment opportunities, even in the short-run.

However, this process of factor reallocation only occurs in the absence of adjustment costs. This arises from the short-run nature of the productivity shocks examined. Firms in areas with high hiring and firing costs have little incentive to hire workers in response to year-to-year changes in temperature, and workers may expect fewer employment opportunities in these regions, increasing search costs. Exploiting spatial variation in, and firm-level exposure to, India's labour regulation environment I show an absence of labour reallocation in areas with a pro-worker labour regulation environment, following an increase in temperature. Consequently, manufacturing production in these areas is only affected by the remaining contractionary effects of temperature increases.

Future research aims to understand whether in areas that have flexible labour market environment other factors impede reallocation, and the degree to which the burden of these broader adjustment costs fall on workers. In addition it is important to build upon our understanding about the interpretation of the remaining contractionary effects of inclement weather and explore the opportunities and constraints that firms face in mitigating these losses – to minimise total welfare losses in situations where market-based resource reallocation is possible, and minimise the direct productivity effects in cases where constraints to market-based resource reallocation are unable to offset productivity losses.

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Table 1: Descriptive Statistics - Manufacturing

	Mean	Std. Dev.	5%	95%	Obs.
Total Output (Million Rs.)	1,405.024	9,342.074	10.446	3,781.618	48,125
Output Per Worker (Million Rs.)	2.819	9.232	0.0529	9.0562	48,125
Employment (Contract Workers)	264.565	1,135.027	16	682	23,886
Contract Worker Average Day Wage (Rs.)	125.166	67.55	52.293	240.71	23,886
Employment (Permanent Workers)	323.085	614.232	24	982	46,494
Permanent Worker Average Day Wage (Rs.)	202.441	132.343	50.788	526.691	46,494
Annual Daily Average Temperature (°C)	25.717	0.235	21.356	28.345	48,125
Growing Season Daily Average Temperature (°C)	24.743	0.265	20.776	27.724	48,125
Non-Growing Season Daily Average Temperature (°C)	28.639	0.461	22.232	31.733	48,125
Total Annual Rainfall (mm)	1,067	200	497	2,216	48,125
Total Growing Season Rainfall (mm)	964	194	455	1,803	48,125
Total Non-Growing Season Rainfall (mm)	153	59	4.2	527	48,125

Notes: 1 Rs. $\approx$ £0.01 $\approx$ \$0.02.

Table 2: Sample Selection

Action Taken	Observations Dropped	Final Sample
Initial Sample	-	371,383
Sectors Outside of Manufacturing	19,884	351,499
Closed Plants	87,873	263,626
Match to 2001 Districts	23,544	240,137
Open for more than 12 months a year	642	239,491
Total Output Zero or Missing	30,275	209,216
All Workers Wage Bill Zero or Missing	786	208,430
Days Worked Zero or Missing	3	208,427
Firms Below Regulation Threshold	155,356	53,071
Drop Union Territories	1,229	51,842
Balance District $\times$ Year Panel	2,742	49,100
Zero Agricultural GDP	975	48,125

Table 3: Descriptive Statistics - Difference in Means

	Pro-Worker States	Control States	Difference [Treatment - Control]
ASI Data			
Total Output	1.343	1.309	0.0343
(Billion Rs.)	(0.0485)	(0.0649)	(0.0935)
Output per Worker	3.352	2.579	0.773***
(Million Rs.)	(0.137)	(0.062)	(0.134)
Employment	179.023	294.273	-115.249***
(Contract Workers)	(3.580)	(11.604)	(18.641)
Average Day Wage	128.882	123.328	5.559***
(Contract Workers)	(0.929)	(0.611)	(1.135)
Employment	350.980	316.276	34.70***
(Permanent Workers)	(8.837)	(3.679)	(8.200)
Average Day Wage	252.052	187.700	64.351***
(Permanent Workers)	(1.948)	(0.891)	(1.922)
Weather Data			
Annual Daily Average	25.794	24.753	1.04***
Temperature (°C)	(0.064)	(0.051)	(0.097)
Growing Season Daily	24.497	23.670	0.827***
Average Temperature (°C)	(0.032)	(0.027)	(0.063)
Non-Growing Season Daily	29.686	28.004	1.682***
Average Temperature (°C)	(0.053)	(0.035)	(0.084)
Total Annual	1,215	1,078	137***
Rainfall (mm)	(10.076)	(5.170)	(16.1)
Growing Season	1,123	953	169***
Rainfall (mm)	(8.469)	(3.961)	(9.817)
Non-Growing Season	90	124	-32***
Rainfall (mm)	(2.224)	(1.690)	(4.005)
Other Characteristics			
Share of Agricultural GDP	17.88	17.95	-0.066
	(0.464)	(0.199)	(0.501)
Share of Manufacturing GDP	10.57	12.15	-1.58***
	(0.372)	(0.201)	(0.491)
Share of Class 1 Cities	0.128	0.109	0.019***
	(0.002)	(0.003)	(0.006)

Table 4: The Effect of Temperature and Rainfall on Agricultural Yields

	(1) Agriculture All Crops	(2) Agriculture All Crops	(3) Agriculture All Crops	(4) Agriculture Kharif Crops	(5) Agriculture Kharif Crops	(6) Agriculture Kharif Crops	(7) Agriculture Rabi Crops	(8) Agriculture Rabi Crops	(9) Agriculture Rabi Crops
Panel A: Annual									
Daily Average	-0.218***		-0.196***	-0.273***		-0.267***	-0.183***		-0.137***
Temperature (°C)	(0.0418)		(0.0419)	(0.0594)		(0.0638)	(0.0476)		(0.0463)
Total Rainfall (100mm)		0.0141***	0.00558*		0.0132***	0.0153		0.0182***	0.0119***
		(0.0387)	(0.0336)		(0.0429)	(0.0402)		(0.0426)	(0.0357)
Panel B: Growing Season									
Growing Daily Average	-0.205***		-0.185***	-0.242***		-0.236***	-0.220***		-0.185***
Temperature (°C)	(0.0319)		(0.0303)	(0.0501)		(0.0535)	(0.0412)		(0.0399)
Non-Growing Daily Average	-0.0247		-0.0265	-0.0412**		-0.0449*	0.0143		0.0196
Temperature (°C)	(0.0188)		(0.0215)	(0.0201)		(0.0233)	(0.0176)		(0.0194)
Growing Season		0.0158***	0.00665*		0.0140***	0.0229		0.0209***	0.0110***
Rainfall (100mm)		(0.0437)	(0.0372)		(0.0483)	(0.0463)		(0.0527)	(0.0413)
Non-Growing Season		0.00618	-0.00330		0.00939	-0.00561		0.0437	0.0755
Rainfall (100mm)		(0.00748)	(0.00888)		(0.00873)	(0.0104)		(0.00914)	(0.00798)
Observations	3,045	3,045	3,045	3,045	3,045	3,045	2,744	2,744	2,744
Adjusted R^2	0.997	0.997	0.997	0.995	0.995	0.995	0.985	0.985	0.985
District Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State-Year Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

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). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 700 km. District distances are computed from district centroids. The distance is selected as providing the most conservative standard errors, looped over all distances between 100 and 1000km.

Table 5: The Effect of Temperature and Rainfall on Agricultural Wages and Employment

	(1) Agriculture - Wages	(2) Agriculture - Share of Employment
Panel A: Annual		
Daily Average	-0.0703***	-0.0574***
Temperature (°C)	(0.0271)	(0.0114)
Total Rainfall (100mm)	-0.00315	-0.00197
	(0.00304)	(0.00188)
Panel B: Growing Season		
Growing Daily Average	-0.0557**	-0.0681***
Temperature (°C)	(0.0281)	(0.0153)
Growing Season	-0.00497	-0.00178
Rainfall (100mm)	(0.00387)	(0.00211)
Non-Growing Daily Average	-0.0194	0.00121
Temperature (°C)	(0.0157)	(0.00865)
Non-Growing Season	0.00124	-0.00672
Rainfall (100mm)	(0.0109)	(0.00559)
Observations	1,879	2,150
Adjusted R^2	0.997	0.964
District Fixed Effects	Yes	Yes
Year Fixed Effects	Yes	Yes
State-Year Time Trends	Yes	Yes

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). Spatial autocorrelation is assumed to linearly decrease in distance up to a cutoff of 400 km. District distances are computed from district centroids. The distance is selected as providing the most conservative standard errors, looped over 100 and 1000km.

Table 6: The Net Effects of Temperature and Rainfall on Manufacturing Production, Employment, and Wages

	(1) Total Output	(2) Output Per Worker	(3) Day Wage Contract	(4) Day Wage Permanent	(5) Employment Contract	(6) Employment Permanent
Daily Average Temperature (°C)	0.000906	-0.00612	-0.0286**	-0.0158	-0.00711	0.0221
	(0.0303)	(0.0304)	(0.0132)	(0.0225)	(0.0252)	(0.0281)
Annual Rainfall (100mm)	-0.00500	-0.00464	-0.00198	-0.00139	-0.00156	0.00349
	(0.00367)	(0.00315)	(0.00270)	(0.00180)	(0.00514)	(0.00318)
District × Sector FE	yes	yes	yes	yes	yes	yes
Sector × Year FE	yes	yes	yes	yes	yes	yes
State-Year Time Trends	yes	yes	yes	yes	yes	yes
Observations 48,125	48,125	23,886	46,494	23,886	46,494	
Adjusted R^2 0.452	0.498	0.391	0.611	0.313	0.335	

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Robust Standard errors, clustered at the State level, are in parentheses.

Table 7: The Differential Effects of Temperature on Manufacturing Production, Employment, and Wages

	(1) Total Output	(2) Output Per Worker	(3) Day Wage Contract	(4) Day Wage Permanent	(5) Employment Contract	(6) Employment Permanent
Daily Average Temperature (°C)	0.0270	0.0164	-0.0305**	0.00423	0.0240	0.0326
	(0.0280)	(0.0295)	(0.0135)	(0.0165)	(0.0224)	(0.0285)
DAT × Pro-Worker	-0.0981***	-0.0847**	0.0488***	-0.0743***	-0.114***	-0.0392
	(0.0301)	(0.0374)	(0.0133)	(0.0131)	(0.0359)	(0.0349)
Rainfall Controls	yes	yes	yes	yes	yes	yes
District × Sector FE	yes	yes	yes	yes	yes	yes
Sector × Year FE	yes	yes	yes	yes	yes	yes
State-Year Time Trends	yes	yes	yes	yes	yes	yes
Direct Effect	-0.071***	-0.068**	0.018	-0.0700***	-0.0900**	-0.006
	(0.0202)	(0.0316)	(0.0129)	(0.0108)	(0.0344)	(0.0330)
Factor Reallocation Effect	0.0981***	0.0847**	-0.0488***	0.0743***	0.114**	0.0392
	(0.0301)	(0.0374)	(0.0133)	(0.0131)	(0.0359)	(0.0349)
Observations	48,125	48,125	23,886	46,494	23,886	46,494
Adjusted R^2	0.452	0.498	0.392	0.611	0.313	0.335

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Robust Standard errors, clustered at the State level, are in parentheses.

Table 8: The Effects of Temperature On Manufacturing Firms Below the Regulatory Threshold

	(1) Total Output	(2) Output Per Worker	(3) Day Wage Contract	(4) Day Wage Permanent	(5) Employment Contract	(6) Employment Permanent
Daily Average Temperature (°C)	0.0622*	0.0352	0.00918	0.0243**	-0.0386	0.0211
	(0.0323)	(0.0254)	(0.0138)	(0.0111)	(0.0288)	(0.0195)
DAT × Pro-Worker	0.121*	0.00582	-0.0196	0.00744	0.0829	0.0749
	(0.0663)	(0.0448)	(0.0188)	(0.00987)	(0.0501)	(0.0507)
Rainfall Controls	yes	yes	yes	yes	yes	yes
District × Sector FE	yes	yes	yes	yes	yes	yes
Sector × Year FE	yes	yes	yes	yes	yes	yes
State-Year Time Trends	yes	yes	yes	yes	yes	yes
Observations	135,407	135,407	35,115	125,421	35,115	125,421
Adjusted R^2	0.316	0.385	0.458	0.427	0.379	0.236

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Robust Standard errors, clustered at the State level, are in parentheses.

Table 9: The Differential Effects of Temperature On Manufacturing - Alternative Definitions of the Labour Regulation Environment

	(1) Total Output	(2) Output Per Worker	(3) Day Wage Contract	(4) Day Wage Permanent	(5) Employment Contract	(6) Employment Permanent
Panel A: Permissions						
Daily Average Temperature (°C)	0.0113	0.000415	-0.0272**	-0.00280	0.00888	0.0353
	(0.0306)	(0.0328)	(0.0112)	(0.0176)	(0.0267)	(0.0266)
DAT × Pro-Worker (Alt 1)	-0.0557*	-0.0349	0.0459***	-0.0683***	-0.0737**	-0.0693*
	(0.0279)	(0.0243)	(0.0144)	(0.0122)	(0.0333)	(0.0380)
Panel B: Thresholds						
Daily Average Temperature (°C)	0.0126	0.00593	-0.0193	-0.0107	0.00243	0.0198
	(0.0289)	(0.0276)	(0.0139)	(0.0227)	(0.0239)	(0.0288)
DAT × Pro-Worker	-0.150***	-0.154***	0.0384*	-0.0642***	-0.171***	0.0288
	(0.0356)	(0.0367)	(0.0218)	(0.0197)	(0.0488)	(0.0273)
Panel C: Pro-Employer						
Daily Average Temperature (°C)	0.0213	0.0126	-0.0201	0.00714	0.0289	0.0237
	(0.0346)	(0.0372)	(0.0147)	(0.0197)	(0.0228)	(0.0379)
DAT × Pro-Worker	-0.0917**	-0.0804*	0.0361**	-0.0776***	-0.120***	-0.0290
	(0.0364)	(0.0439)	(0.0154)	(0.0176)	(0.0307)	(0.0420)
DAT × Pro-Employer	0.0202	0.0138	-0.0469*	-0.0104	-0.0222	0.0321
	(0.0357)	(0.0326)	(0.0266)	(0.0181)	(0.0586)	(0.0438)
Panel D: Court Efficiency						
Daily Average Temperature (°C)	0.0281	0.0173	-0.0304**	0.00265	0.0232	0.0335
	(0.0269)	(0.0287)	(0.0135)	(0.0168)	(0.0216)	(0.0282)
DAT × Court Efficiency	-0.210***	-0.181**	0.103***	-0.140***	-0.235***	-0.0865
	(0.0482)	(0.0653)	(0.0280)	(0.0319)	(0.0638)	(0.0852)
Panel D: Court Cases Per Worker						
Daily Average Temperature (°C)	0.0214	0.0106	-0.0297**	0.00318	0.0194	0.0339
	(0.0290)	(0.0305)	(0.0130)	(0.0165)	(0.0236)	(0.0282)
DAT × Court Cases Per Worker	-0.0970**	-0.0790*	0.0546***	-0.0886***	-0.116**	-0.0553
	(0.0395)	(0.0431)	(0.0172)	(0.0162)	(0.0422)	(0.0345)
Rainfall Controls	yes	yes	yes	yes	yes	yes
District × Sector FE	yes	yes	yes	yes	yes	yes
Sector × Year FE	yes	yes	yes	yes	yes	yes
State-Year Time Trends	yes	yes	yes	yes	yes	yes

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Robust Standard errors, clustered at the State level, are in parentheses.

Table 10: The Differential Effects of Temperature On Manufacturing - Alternative Weather Measures

	(1) Total Output	(2) Output Per Worker	(3) Day Wage Contract	(4) Day Wage Permanent	(5) Employment Contract	(6) Employment Permanent
Panel A: CDD (Piecewise Function)						
Annual CDD (100 days)	0.00817	0.00706	-0.00521	0.0103	-0.0181	-0.00212
$t_L = 0, t_H = 22$	(0.0159)	(0.0168)	(0.00727)	(0.00677)	(0.0172)	(0.0101)
Annual CDD (100 days)	0.00506	0.00210	-0.00951**	-0.00273	0.0171*	0.0131
$t_L = 22, t_H = \infty$	(0.00848)	(0.00811)	(0.00443)	(0.00600)	(0.00893)	(0.00823)
CDD_{low} × Pro-Worker	0.0175	0.000578	0.0110	-0.0201**	0.0382	0.0169
	(0.0204)	(0.0200)	(0.0132)	(0.00801)	(0.0652)	(0.0133)
CDD_{high} × Pro-Worker	-0.0380***	-0.0278**	0.0129**	-0.0198***	-0.0475***	-0.0211*
	(0.0123)	(0.0122)	(0.00594)	(0.00432)	(0.0105)	(0.0105)
Panel B: CDD (Hot Days)						
Annual CDD (100 days)	0.00555	0.00248	-0.00988**	-0.00226	0.0158*	0.0130
$t_L = 22, t_H = \infty$	(0.00852)	(0.00826)	(0.00432)	(0.00612)	(0.00857)	(0.00846)
CDD × Pro-Worker	-0.0356**	-0.0273**	0.0137**	-0.0215***	-0.0445***	-0.0193*
	(0.0128)	(0.0130)	(0.00522)	(0.00442)	(0.0101)	(0.0101)
Panel C: Moisture Availability Index						
log(Moisture Availability Index)	-0.0532**	-0.0659**	0.0417**	0.000159	-0.0464	-0.0210
	(0.0243)	(0.0284)	(0.0185)	(0.0148)	(0.0351)	(0.0297)
log(MAI) ×	0.0635	0.0503	-0.0165	0.0520***	0.223***	0.0544
Pro-Worker	(0.0590)	(0.0888)	(0.0188)	(0.0176)	(0.0438)	(0.0426)
Rainfall Controls	yes	yes	yes	yes	yes	yes
District × Sector FE	yes	yes	yes	yes	yes	yes
Sector × Year FE	yes	yes	yes	yes	yes	yes
State-Year Time Trends	yes	yes	yes	yes	yes	yes

Notes: The Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Robust Standard errors, clustered at the State level, are in parentheses.

Table 11: The Differential Effects of Temperature On Manufacturing - Pre- and Post-Harvest

	(1) Total Output	(2) Output Per Worker	(3) Day Wage Contract	(4) Day Wage Permanent	(5) Employment Contract	(6) Employment Permanent
Pre-Harvest Temperature	0.0181	0.00325	-0.0226	0.00118	0.0514**	0.0201
	(0.0259)	(0.0250)	(0.0161)	(0.0133)	(0.0192)	(0.0207)
PHT × Pro-Worker	-0.0933**	-0.0619*	0.0212	-0.0444***	-0.120***	-0.0528*
	(0.0347)	(0.0331)	(0.0138)	(0.0114)	(0.0269)	(0.0268)
Harvest Temperature	0.0141	0.0117	-0.00953	0.00846*	-0.00476	0.00905
	(0.0113)	(0.0141)	(0.0102)	(0.00687)	(0.0145)	(0.0208)
HT × Pro-Worker	-0.0133	-0.0284**	0.0245***	-0.0309***	0.00313	0.00592
	(0.0166)	(0.0117)	(0.00834)	(0.00810)	(0.0349)	(0.0169)
Rainfall Controls	yes	yes	yes	yes	yes	yes
District × Sector FE	yes	yes	yes	yes	yes	yes
Sector × Year FE	yes	yes	yes	yes	yes	yes
State-Year Time Trends	yes	yes	yes	yes	yes	yes
Observations	48,125	48,125	23,886	46,494	23,886	46,494
Adjusted R^2	0.451	0.497	0.377	0.611	0.313	0.335

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Robust Standard errors, clustered at the State level, are in parentheses.

Table 12: The Effect of Temperature on Exports

	(1) Manufacturing Exports	(2) Agricultural Exports	(3) Manufacturing Exports	(4) Agricultural Exports
Annual Daily Average Temperature (° C)	-0.0217***	-0.0327***	-0.0108*	-0.0315***
	(0.00620)	(0.00400)	(0.00584)	(0.00379)
DAT × Pro-Worker	–	–	-0.126***	-0.0392
			(0.00955)	(0.0410)
Rainfall Controls	yes	yes	yes	yes
District × Sector FE	yes	yes	yes	yes
Sector × Year FE	yes	yes	yes	yes
State-Year Time Trends	yes	yes	yes	yes
Direct Effect	–	–	-0.136***	-0.0707*
			(0.00973)	(0.0407)
Factor Reallocation Effect	–	–	0.126***	0.0392
			(0.00955)	(0.0410)
Observations	756,672	756,672	756,672	756,672
Adjusted R^2	0.882	0.127	0.971	0.127

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Robust Standard errors, clustered at the State level, are in parentheses.

Table 13: The Effect of Temperature on District GDP - By Sector

	(1) Total GDP	(2) Agricultural GDP	(3) Manufacturing GDP	(4) Tradable Services GDP	(5) Non-Tradable Services GDP
Daily Average Temperature (°C)	-0.0368***	-0.140**	-0.0849***	-0.0211**	-0.00267
	(0.0135)	(0.0620)	(0.0285)	(0.0106)	(0.0119)
DAT × Pro-Worker	0.00563	0.0717	-0.104**	-0.0248	-0.0236
	(0.0418)	(0.130)	(0.0484)	(0.0316)	(0.0403)
District FE	yes	yes	yes	yes	yes
Year FE	yes	yes	yes	yes	yes
State-Year Time Trends	yes	yes	yes	yes	yes
Observations	2,856	2,856	2,856	2,856	2,856
Adjusted R^2	0.999	0.999	0.999	0.999	0.999

Notes: Significance levels are indicated as * 0.10 ** 0.05 *** 0.01. Conley (1999) Standard errors allowing for unknown forms of spatial correlation up to 500km, are in parentheses.

Appendix A - Data Appendix

To be completed...

Manufacturing Output, Employment, and Wages

Data on Manufacturing is constructed at the district level from factory level data provided by the **Annual Survey of Industries** (ASI). The outcome variables of interest are defined by the ASI as follows:

Total Output - the total value of products and by-products manufactured as well as other receipts such as: receipts from non-industrial services rendered to others; work done for others on materials supplied by them; value of electricity produced and sold; sale value of goods sold in the same condition as purchased; addition in stock of semi-finished goods and own construction.

Workers - all persons employed directly, or through any agency, whether for wages or not and engaged in any manufacturing process, or in cleaning any part of the machinery or premises used for manufacturing process, or in any other kind of work incidental to or connected with the manufacturing process or the subject of the manufacturing process. Labour engaged in the repair and maintenance, or production of fixed assets for the factory's own use, or employed for generating electricity, or producing coal, gas, etc. are included.

Wages and Salaries - all remuneration in monetary terms and also payable more or less regularly in each pay period to workers as compensation for work done during the accounting year. It includes: (i) direct wages and salary, i.e., basic wages/salaries, payment for overtime, dearness, compensatory allowance, house rent and other allowances); (ii) remuneration for the period not worked, i.e., basic wages, salaries and allowances payable for leave period, paid holiday, lay-off payments and compensation for unemployment, if not paid from sources other than employers; (iii) bonuses and ex-gratia payment paid both at regular and less frequent intervals, i.e., incentive bonuses, good attendance bonuses, productive bonuses, profit sharing bonuses, festival or year-end bonuses, etc. It excludes lay off payments which are made from trust or other special funds set up exclusively for this purpose, i.e., payments not made by the employer. It also excludes the imputed value of benefits in kind, employer's contribution to old age benefits and other social security charges, direct expenditure on maternity benefits and créchoes, and other group benefits. Travelling and other expenditure incurred for business purposes and reimbursed by the employer are excluded. The wages are expressed in terms of gross value i.e., before deduction for fines, damages, taxes, provident fund, employee's state insurance contribution, etc.

Appendix B - Seasonal Migration and Employment in India: Some Stylized Facts

In round 64 of the National Sample Survey a special schedule was included on seasonal migration. This appendix provides a brief summary of the behaviour exhibited by these seasonal migrants and the households they come from. In addition to seasonal migration we examine the employment activities of workers in rural areas to understand the importance of the formal manufacturing sector in these areas. This captures an important, yet subtle point, that workers may switch between agriculture and manufacturing without migrating, that is they may commute. By focussing solely on seasonal migration, we would underestimate the importance of manufacturing as a rural employment opportunity.

We begin by examining the employment characteristics of households in rural and urban India and then examine patterns in seasonal migration.

Table A1: Employment Activities in India

	Rural	Urban	Combined
Agricultural Employment	66.73%	11.58%	49.53%
Manufacturing Employment	14.07%	39.3%	22.28%
Construction Employment	6.64%	9.50%	7.55%
Services Employment	11.93%	38.63%	19.93%
Mining Employment	0.61%	0.95%	0.68%

Table A1 presents the breakdown of employment activities in rural and urban India. As one might expect agricultural employment dominates most rural employment accounting for 67% of the workforce. However, manufacturing accounts for nearly 15% a substantial fraction. In urban areas manufacturing accounts for nearly 40% of employment, closely followed by services that accounts for close to 39% of employment. The 12% share of employment in "urban" classified areas highlights the limitations associated with India's simplified classification of urban areas.

One of the most striking features associated with India's spatial development is the expansion of India's metropolitan areas into rural areas referred to as peri-urbanization. In the last decade alone there has been an official increase in urban agglomerations by 25%, with population shifting outwards. This is further exemplified by the rapid expansion of India's night lights during this period. While there has been a substantial increase in the intensity of night lights since 2001, there is also evidence of substantial urban sprawl.[23]

[23]It is important to note that as the intensity of night light increases, there will be an increase in light

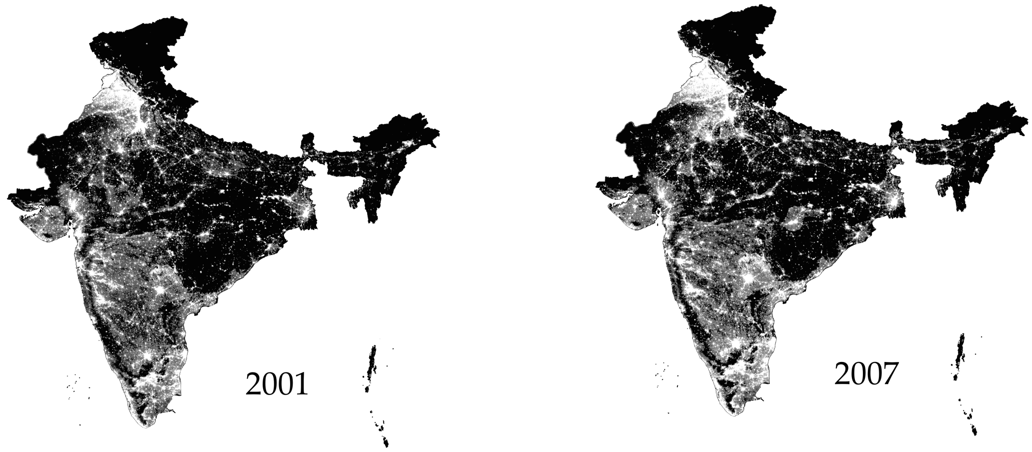


Figure 1: The Night Lights of India (2001 - 2007)

This process of peri-urbanization reduces the costs of rural-urban migration as manufacturing plants shift production to sub-urban fringes. Henderson (2010) presents evidence in support of this industrial decentralisation for the Republic of Korea and Japan. Desmet et al. (2012) and Ghani et al. (2012) also provide supporting evidence for this process in India. Desmet et al. (2012) 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 into districts which originally were less concentrated. This is suggestive of decentralisation in the manufacturing sector. Ghani et al. (2012) look more specifically at the manufacturing sector and document it's movement away from urban to rural areas, comparing the formal and informal sectors. The authors argue that the formal sector is becoming more rural; however, in practice, a lot of this movement is likely sub-urbanisation, rather than ruralisation, in which firms move to the outskirts of cities where they can exploit vastly cheaper land and somewhat cheaper labour.

This 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 seasonal workers choosing to commute from home, rather than migrate to the city. This is consistent with the non-trivial shares of manufacturing employment and agricultural employment presented in rural and urban areas respectively.

In terms of migration only 2.67% of households reported to have moved in the last year. Table A2 provides a summary of this migration.[24]

pollution, resulting in misattribution of urban activity to neighbouring areas. As a consequence of this, night light images should be adjusted to account for this overglow bias (Abrahams, Lozano-Gracia, and Oram, 2014). In the absence of this adjustment, we can consider the differences as an upper bound for the classification and reclassification of urban areas over time.

[24]To provide some context, roughly 10% of household migrate internally within the United States every

Table A2: Non-Seasonal Migration in India

	Rural	Urban	Combined
Migrated to the area in the last year	2.38%	3.23%	2.67%
Permanent Migration	36.94%	46.72%	41.07%
Destination:			
Within District	56.56%	41.23%	50.13%
Within State (Different District)	22.39%	32.64%	26.70%
Out of State	20.62%	25.39%	22.62%
Out of Country	0.42%	0.74%	0.55%
Reason:			
Employment	79.88%	82.16%	80.83%
Education	6.75%	6.42%	6.61%
Marriage	3.61%	1.59%	2.77%
Displacement	4.02%	4.26%	4.12%
Other	5.73%	5.57%	5.66%

Table A2 shows that on average over 50% of non-seasonal migration was within district with just under 60% accounting for temporary migration. When accounting for migration within-state this accounts for almost 80% of migration, with the remaining migration flowing from out of state (22.62%) and from out of the country (0.55%). Employment reasons, defined to include both the search and uptake of employment, account for nearly 80% of the motivation behind migration decisions.

In contrast to broader forms of temporary and permanent migration, around 14% of the households sampled in the National Sample Survey reportedly send out a member of the family as a seasonal migrant. This is over 5 times more than the proportion of households that had reportedly migrated to the area in the last year, either as a temporary or permanent migrant. In the context of this paper it seems most likely that seasonal migrants are the relevant population of interest. Seasonal Migrants are defined as members of the household that are away from the home for more than 1 month but less than 6 months at a time. Table A3, provides a breakdown of the origin of these seasonal migrants and their destination behaviours. Table A4, provides a breakdown of the activities that seasonal migrants engage in.

year demonstrating the significantly low levels of internal migration observed in India.

Table A3: Seasonal Migration in India - Location

	Rural	Urban	Combined
Origin	83.4%	16.6%	–
Destination:			
Within District	23.74%	20.98%	23.28%
Within State (Different District)	33.96%	42.58%	35.39%
Out of State	41.49%	34.03%	40.25%
Out of Country	0.81%	2.41%	1.07%

From Table A2, we observe that just under 60% of seasonal migration occurs within-state with the remaining 40% occurring between states and a very small percentage (roughly 1%) occurring between countries. Of this migration around 23% is within district accounting for nearly 40% of within-state migration. This is remarkable when one considers that each state has an average of 27 districts.

Table A4: Seasonal Migration in India - Activity

	Rural	Urban	Combined
Engaged in Economic Activity	87.12%	77.57%	85.53%
Destination Sector:			
Agriculture	17.84%	7.01%	16.25%
Manufacturing	25.24%	35.47%	26.78%
Services	16.14%	28.96%	18.06%
Construction	38.35%	26.92%	36.63%
Mining	2.36%	1.61%	2.25%

Around 85% of seasonal migrants report to be engaged in economic activity.[25] This is substantial indicating that seasonal migration is driven by demand for employment rather than other migration drivers. We observe that the majority of migrants work in construction. However, of interest for the focus of this paper, the manufacturing sector is the destination of nearly 27%. This is 10 percentage points greater than the share of migrants that migrate for work in agriculture.

Combined these summary statistics provide supporting evidence for the mechanism discussed in the paper. The relevant stylised facts are that: 85% of seasonal migrants come from

[25] This is based on the number of non-missing observations from reported industry. Therefore, this number should be treated as a lower bound as some migrants may have failed to report this answer while still engaging in economic activity.

rural areas, where agriculture is the largest employer; close to 60% of seasonal migration is within-state, of which 40% of this rellocation is within the same district; and most importantly, the manufacturing sector comprises the second largest destination sector for seasonal migrants accounting for 25% of employment. As mentioned, seasonal migration provides a lower bound for the sectoral reallocation of labour within-district. Given the expansion of peri-urban areas and the corresponding decentralisation of manufacturing workers may commute from farm to factory without migrating. With manufacturing as the second largest employer in rural areas and the largest employer in urban areas the relationship between these sectors is of first-order interest in examining the functioning of labour markets and production in developing countries.

Appendix C - Weather and Climate in India

Forthcoming...

Figure 2: Daily Average Temperature (1979-2012)

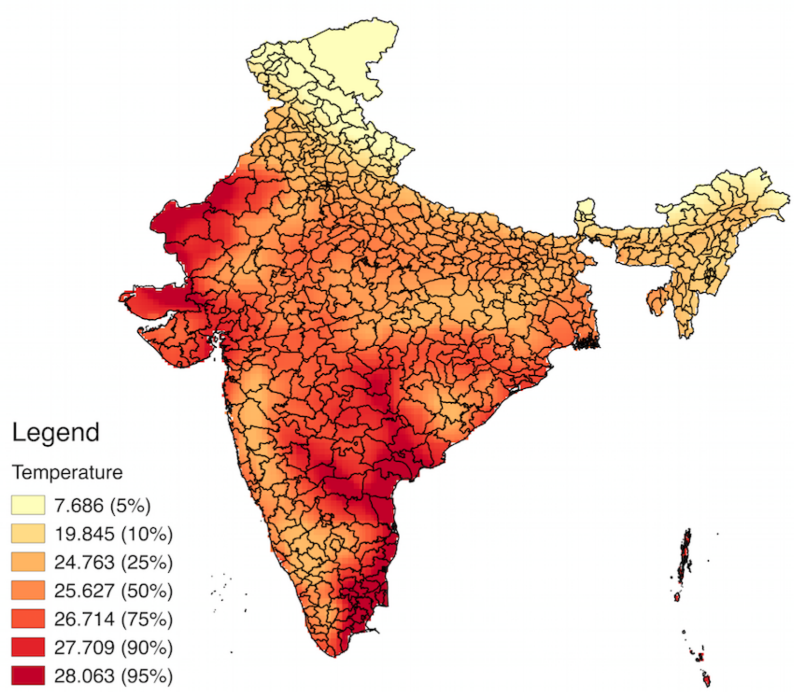


Figure 3: Average Annual Rainfall (1979-2012)

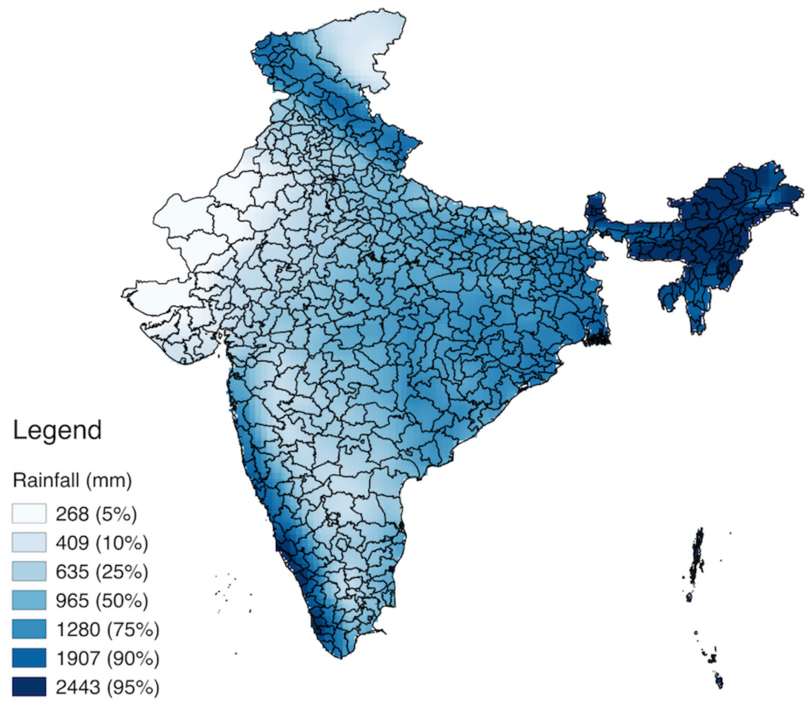
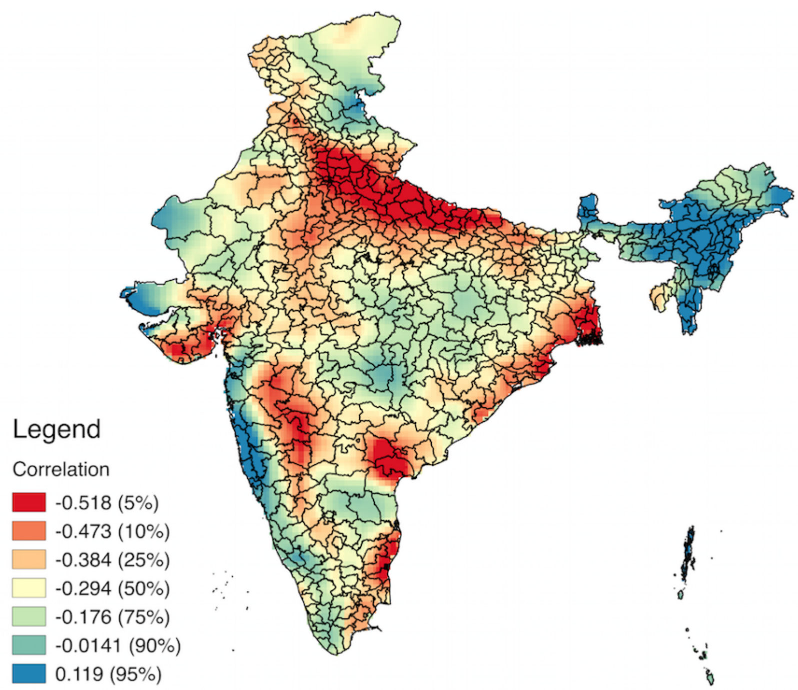


Figure 4: The Correlation between Rainfall and Temperature (1979-2012)



Appendix D - Agriculture in India.

Forthcoming. . .