Firms and Farms: The Impact of Agricultural Productivity on the Local Indian Economy

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Abstract

How do agricultural productivity shocks propagate through the local economy and affect firms? I combine firm, household and district-level data from India, and exploit weather-induced agricultural volatility, to estimate the response of manufacturing firms to changes in agricultural productivity. I show that negative agricultural productivity shocks reduce firm production and employment. This holds true even though the local wage decreases. The effect is driven by firms that produce locally-traded goods, suggesting that the decrease in local demand induced by lower incomes plays a key role. I then examine whether the introduction of a large-scale rural workfare program affects the response of the local economy to agricultural volatility. I show that the program acts as a stabilization policy and attenuates the pro-cyclical response of local wage, consumption, and firms' outcomes to agricultural productivity shocks. The results highlight the importance of local rural demand for a large share of manufacturers and underscore how rural development policies that target households can strongly affect the industrial sector because of general equilibrium effects.

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1 Introduction

Many firms in the developing world operate in economies that are primarily agricultural, where a large fraction of the population resides in rural areas and agriculture accounts for a substantial share of production and employment. In 2005, 70% of all manufacturing establishments in India were located in rural areas and employment in these establishments accounted for 60% of total Indian manufacturing employment[1]. Given these magnitudes, it is natural to ask how conditions in the rural economy affect firms and, in particular, whether rural incomes matter in determining the demand that firms face. This question is the focus of a classical literature that examines the role of market size for industrialization (e.g. Murphy et al., 1989a, 1989b). It is also at the core of a large literature on the role of agricultural development in the growth of the non-farm sector. Some scholars have argued that increases in agricultural productivity are a pre-condition for industrial development, and classical models of structural transformation have formalized this by showing how productivity growth can generate demand for manufacturing goods[2]. A different strand of the literature, on the other hand, stressed the key distinction between open and closed economies, and noted how in open economies an increase in agricultural productivity can in fact crowd-out industrial production because manufacturing has to compete with the agricultural sector for labor [3].

This long-standing question has renewed importance for developing countries today, as the reduction in transportation costs and the consequent increased mobility of goods and factors may have changed the influence of local conditions. In particular, do local rural incomes play an important role in determining the economic opportunities of firms, or do integrated factor and product markets make local incomes irrelevant?

In this paper, I provide direct evidence on this question by examining the dependence of firms on the local rural economy in the context of India. The analysis entails two intertwined parts. First, I exploit weather-induced agricultural productivity fluctuations to study how changes in agricultural incomes affect firms. Second, I take advantage of the introduction in rural areas of a large-scale workfare program, the National Rural Employment Guarantee Act (NREGA), and assess the effects it had on rural incomes and wages, and how these effects translated to the rural industrial sector.

To guide the empirical analysis, I provide a simple multi-sector general equilibrium

[1] Author's calculations based on data from the Annual Survey of Industries and National Sample Survey (Schedule 2.2, Manufacturing Enterprises) for the year 2005-2006.

[2] See Rosenstein-Rodan, 1943; Lewis, 1954; Rostow, 1960; Ngai and Pissarides (2007), Baumol (1967), Kongsamut, Rebelo and Xie (2001), Gollin, Parente and Rogerson (2002).

[3] See Matsuyama (1992), Foster and Rosenzweig (2004, 2008).

model of the local economy that illustrates how agricultural productivity shocks affect the local economy and are transmitted to firms through factor and product markets. I then extend the model to characterize how the introduction of a workfare program affects this transmission and impacts firms.

I model an economy with three distinct productive sectors: agriculture, a tradable non-farm sector and a non-tradable non-farm sector. Agricultural goods are assumed to be traded across space, while goods in the non-farm sector are either traded across space or sold locally. The distinction between firms that sell traded vs. non-traded goods is crucial because firms will be affected differently by changes in local conditions. Consider a positive shock to agricultural productivity. This has two effects on local firms: on the one hand, it induces an increase in the cost of labor because increased demand for labor in agriculture raises the equilibrium wage. On the other hand, it positively affects local incomes and thus potentially the demand that firms face. Firms that sell goods in global markets are only affected by the first channel (*wage channel*) and their activity will be crowded-out by increases in agricultural productivity. Firms that sell their goods to local households will instead also benefit from the second channel (*demand channel*) and their activity may in fact be crowded-in by increases in agricultural productivity.

The model derives predictions for the local effects of agricultural productivity on equilibrium wage, income, and consumption, as well as sectoral employment, production and prices. The model predictions are then examined using a unique combination of firm, household and district-level data from India. The empirical analysis requires a source of exogenous variation in agricultural productivity. I rely on the fact that in rural India a large fraction of agriculture is rainfed and agricultural productivity depends highly on monsoon rainfall. Variation in rainfall realizations across Indian districts and over time is used to estimate the response of equilibrium outcomes to agricultural productivity.

The first main result of the paper is that local rural incomes are an important determinant of the demand that firms face. I show that firms respond to a negative agricultural productivity shock by reducing production and employment. This holds true even though the local wage decreases, suggesting that, while both effects are at play, the demand effect more than compensate the wage effect. I also show that, consistently with the model, the result is driven by firms that produce locally-traded good, while firms that produce traded goods increase their activity, although the estimated elasticity is not statistically significant. This set of results illustrates how an economically important share of firms does not rely on national, or even state-level markets. We may have expected the mobility of goods and factors to be sufficient to limit the influence of local conditions. The evidence in this paper shows that this is not that case and that, instead, local rural incomes continue to play an important role in determining the economic opportunities of firms.

Understanding how firms are affected by the conditions in the local economy has important policy implications. Researchers and policymakers interested in firms in low-income countries generally focus their attention on policies that affect firms directly. The mechanisms I describe, on the other hand, underscore how policies targeted to the agricultural sector or aimed at rural households may have important consequences for firms because of their general equilibrium implications. Ignoring these general equilibrium effects can lead to a partial, and possibly misleading, assessment of the impact of policies. In the second part of this paper, I provide direct evidence for the policy relevance of linkages in the local economy, and examine the impact of a large-scale workfare program, the National Rural Employment Guarantee Act (NREGA), introduced in rural India in 2006.

The program entitles every household in rural India to 100 days of minimum-wage public employment per year. The type of work generated by the program is low-wage, unskilled manual work, often in construction. According to government administrative data, during 2010-2011, the program generated a total of 2.3 billion person-days of employment, providing employment to 53 million households in rural India[4]. The size of the program makes it one of the largest and most ambitious public-works employment schemes ever attempted in history.

In this part, I take advantage of the timing of NREGA implementation across districts to assess how the program affected the local economy and firms. I introduce NREGA in the model as an additional sector that hires at a fixed wage (the program statutory wage) and obtain predictions for the impact of the program on equilibrium wage, income and sectoral outcomes. Intuitively, the availability of public employment guarantees to local workers the possibility to be remunerated at the NREGA wage. This induces a wage floor, that is, it prevents the equilibrium wage from falling below the NREGA wage during times of low agricultural productivity. Because of its stabilization effect on local wage, the program may also stabilize local income and demand. That is, it may be able to support consumption during local downturns and behave as a counter-cyclical stimulus policy. This, in turn, may stabilize industrial production and employment.

In the empirical analysis, I estimate the response of equilibrium outcomes to agricultural productivity before and after the introduction of NREGA. The comparison of elasticities before and after the program allows me to assess whether NREGA changes

[4]Figures are from the official NREGA website nrega.nic.in.

the way in which agricultural productivity shocks affect the local economy.

The second main finding of the paper is that NREGA, through its effects on local wage and demand, affects firms. I show that the program acts as a local stabilization policy and attenuates the pro-cyclical response of local wage, consumption, and firms' outcomes to agricultural productivity shocks. The evidence supports the mechanisms outlined in the model. First, I show that public employment under NREGA strongly responds to adverse agricultural shocks. That is, workers resort to NREGA to a larger extent when the local economy is hit by worse agricultural productivity shocks. This provides evidence for the key channel through which the stabilization effect of NREGA is operating. Second, I show that local rainfall has a much smaller impact on local wage and consumption after the introduction of the program, even though it continues to have an impact on agricultural productivity. This suggests that NREGA acts on the relationship between agricultural productivity and local income, and attenuates the response of the latter to shocks. Finally, I show that, because of its effect on local income, the program attenuates the relationship between agricultural productivity and firms' production and employment.

This paper relates to previous work in multiple literatures. First, it relates to a classical literature that examines the role of agricultural productivity in the development of the non-farm sector[5]. This paper is most closely linked to the more recent work in this literature, which empirically tests how improvements in agricultural productivity affect the rest of the economy (Foster and Rosenzweig, 2004; Hornbeck and Keskin, 2012; Bustos et al., 2013; Marden, 2015).

Second, in the literature on NREGA, this paper is most closely related to Imbert and Papp (2015), Berg et al. (2013) and Zimmerman (2014), that study the impact of NREGA on wages, and Fetzer (2014), that shows that NREGA reduced conflict by attenuating the relationship between rainfall and violence. While there is a growing literature on NREGA, only few papers consider its general equilibrium implications, and those that do only focus on the impact on wages. My work shows that it is crucial to consider also the impact that the program had on demand and prices of goods sold locally. This is important because the effect of the program on demand can more than compensate its effect on wage and, as I show, result in a crowd-in of local economic activity in the non-farm sector. To the best of my knowledge, no previous work has examined whether and how workfare programs, including NREGA, affect the industrial sector. The closest paper in this regard is Magruder (2013), which used the timing of increase in minimum wages

[5]See Rosenstein-Rodan, 1943; Schultz, 1953; Lewis, 1954; Rostow, 1960

across Indonesian provinces in the 1990s to test the predictions of a big push model.

Third, this paper relates to a large literature in development economics on the productivity risk that households in low-income countries face, the extent to which they are insured against such risk and their consumption smoothing capabilities (e.g. Binswanger and Rosenzweig, 1993; Townsend, 1994; Udry, 1994). In this literature, this paper is most closely related to Jayachandran (2006), which shows how poverty, low mobility and credit constraints exacerbate productivity risk. Her framework only considers the agricultural sector. I build on that framework adding the non-farm sector to the analysis, and showing how the cross-sector linkages in the local economy can be additional sources of productivity risk exacerbation.

Fourth, the analysis and the predictions on tradable vs. non-tradable sectors are related to the recent literature on trade and volatility (Burgess and Donaldson, 2010; Allen and Atkin; 2015), which shows how trade integration can affect the volatility faced by local households.

More broadly, this work connects to the economics literature on local economic growth (Busso, Gregory, and Kline, 2013; Autor, Dorn, and Hanson 2013; Alcott and Keniston, 2015; Moretti, 2010, 2011) and to the macro literature on the role of sector-specific shocks in macro fluctuations (Acemoglu et al., 2012; Caliendo et al., 2015).

The rest of the paper proceeds as follows. Section 2 presents a model of the local economy to derive the local effects of agricultural productivity shocks and to illustrate the implications of the introduction of NREGA. Section 3 explains the various sources of data used and how the key variables are constructed. Section 4 provides a brief background on NREGA. Section 5 develops the empirical strategy that is used to identify the impact of agricultural productivity on the local economy and the role of NREGA. Section 5 presents the results. Section 6 concludes.

2 Model

In this section I present a simple multi-sector general equilibrium model of the local rural economy to guide the empirical work. The purpose of the model is twofold. First, I illustrate how shocks to the local farm-sector are transmitted to the non-farm economy through linkages in the labor and goods market. In particular, I show how agricultural shocks have different effects on firms that produce traded vs. non-traded goods, because of the key role that local agricultural income plays for the demand of non-traded goods. Second, I illustrate the implications that the introduction of a public-works program has for the response of the local economy to agricultural volatility.

The model draws from Jayachandran (2006), Foster and Rosenzweig (2004) and Matsuyama (1992), and provides predictions that are the object of the empirical analysis.

2.1 A Multi-Sector Model of the Local Rural Economy

2.1.1 Setup

Consider a small open economy (district) with three productive sectors: agriculture, non-farm tradable sector and non-farm non-tradable sector, indexed by $j = \{A, M, S\}$ respectively.

Each sector is modeled as a representative firm and produces output Y_j using labor n_j. The production functions are $Y_j = \theta_j n_j^{\alpha}$, where $\theta_j > 0$ represents a sector-specific productivity parameter. Productivity in the agricultural sector, θ_A, captures weather-related productivity shocks and is the driving force in the model.

Firms in the agricultural and non-farm tradable sectors sell goods into global markets, so prices p_A and p_M are exogenously given. Firms in the non-tradable sector instead sell goods to local agents, so price p_S is endogenous and determined by local demand conditions.

Labor receives wage w. I assume that labor is immobile across districts but is mobile across sectors. Given local mobility of labor, in equilibrium the wage w will be equated across sectors.

The local economy has a mass one of homogenous agents. Agents are endowed with one unit of time, which I assume they supply inelastically to the labor market. In equilibrium total employment in the three sectors must equal total local labor supply, and equilibrium wage is determined by the labor market clearing condition:

$$n_A + n_M + n_S = 1.$$

Agents in the local economy have Cobb-Douglas preferences over agricultural goods (c_A), traded goods (c_M) and non-traded goods (c_S), with share of non-traded goods equal to γ. Agents receive profits from the agricultural and non-tradable sector, while I assume that profits from the tradable sector do not accrue locally[6]. This is due to the fact that firms in this sector are likely large factories owned by individuals outside the district of interest. In the model, this ensures that a positive shock to agriculture increases

[6] I could alternatively assume that a share $\mu > 0$ of tradable sector profits accrues locally. The key assumption is not $\mu = 0$, but $\mu < 1$.

consumption of non-traded goods instead of increasing wages and price of non-traded goods proportionally.

The budget constraint is thus:

$$\sum_{j\in\{A,M,S\}} p_j c_j = \pi_A + \pi_S + w.$$

Utility maximization with Cobb-Douglas preferences requires the expenditure share on non-traded goods to be equal to γ, so I have:

$$p_s c_s = \gamma\left(\pi_A + \pi_S + w\right).$$

In equilibrium, the price of non-traded goods, p_S, adjusts to equilibrate non-tradable supply and demand, and is determined endogenously to satisfy the market clearing condition:

$$Y_S = c_S.$$

2.1.2 Comparative Statics: The Local Effects of a Change in Agricultural Productivity

In this section I consider the effects of a shock to agricultural productivity on agents and firms in the local economy. I derive the comparative statics for a change in the agricultural productivity parameter θ_A[7].

Given that the wage and the price of the non-traded good must equilibrate their respective markets, it is possible to solve explicitly for the equilibrium wage and the allocation of labor across the three sectors. Specifically, households' utility maximization and firms' profit maximization, together with market clearing, imply that at the competitive equilibrium:

$$w = \frac{\alpha\left[\left(p_A\theta_A\right)^{\frac{1}{1-\alpha}} + C\left(p_M\theta_M\right)^{\frac{1}{1-\alpha}}\right]^{1-\alpha}}{(1-\gamma)^{1-\alpha}} \tag{1}$$

[7]The empirical analysis relies on variation in rainfall R, so that, for any outcome of interest y, I estimate the reduced form impact of rainfall, that is, $\frac{\partial y}{\partial R}$. The assumption implicit to the empirical analysis (which will be tested below) is that agricultural productivity is a function of rainfall, so I can exploit the relation $\frac{\partial y}{\partial R} = \frac{\partial y}{\partial \theta_A}\frac{\partial \theta_A}{\partial R}$. Notice how this implies that the rainfall elasticities estimated are a function of $\frac{\partial \theta_A}{\partial R}$, that is, the strength of the impact that rainfall has on agricultural productivity. In the empirical analysis, I show how such strength depends on the extent of irrigation available in the district.

$$n_j = \frac{(1-\gamma)(p_j\theta_j)^{\frac{1}{1-\alpha}}}{(p_A\theta_A)^{\frac{1}{1-\alpha}} + C(p_M\theta_M)^{\frac{1}{1-\alpha}}} \quad \text{for} \quad j \in \{A, M\} \tag{2}$$

$$n_S = \frac{\gamma\left[(p_A\theta_A)^{\frac{1}{1-\alpha}} + \alpha\,(p_M\theta_M)^{\frac{1}{1-\alpha}}\right]}{(p_A\theta_A)^{\frac{1}{1-\alpha}} + C\,(p_M\theta_M)^{\frac{1}{1-\alpha}}} \tag{3}$$

where $C = 1 - \gamma(1-\alpha)$.

Prediction 1. A positive shock to agricultural productivity θ_A increases the equilibrium wage: $\frac{\partial w}{\partial \theta_A} > 0$.

The result follows immediately from Equation 1. Increases in θ_A increase the marginal return to labor in agriculture, increasing the demand for labor in agriculture and driving up the equilibrium wage. Notice how, by assuming inelastic labor supply, I am excluding the possibility that the increase in wage induces an increase in labor supply, which would in turn mitigate the wage increase. Inelastic labor supply simplifies the analysis but it is not crucial for this result. What is crucial is that labor supply is not fully elastic. If labor supply was fully elastic, changes in agricultural productivity would not affect wages, and all adjustment would occur through migration and/or movement into the labor force.

Prediction 2. A positive shock to agricultural productivity θ_A induces a reallocation of agents towards the local farm sector: $\frac{\partial n_A}{\partial \theta_A} > 0$.

The result follows immediately from Equation 2. It is also immediate to show that agricultural production and profits respond pro-cyclically, that is, $\frac{\partial y_A}{\partial \theta_A} > 0$ and $\frac{\partial \pi_A}{\partial \theta_A} > 0$.

Prediction 3. A positive shock to agricultural productivity θ_A has opposite effects on the tradable and non-tradable components of the local non-farm economy. Specifically:

- *The employment of local tradable firms moves counter-cyclically: $\frac{\partial n_M}{\partial \theta_A} < 0$.*
- *The employment of local non-tradable firms moves pro-cyclically: $\frac{\partial n_S}{\partial \theta_A} > 0$. In addition, the price of non-tradable goods moves pro-cyclically: $\frac{\partial p_S}{\partial \theta_A} > 0$.*

The results follows immediately from Equations 2 and 3, and from the closed-form expression for the equilibrium price of the non-traded good:

$$p_S = \frac{1}{\theta_S}\left[\frac{\gamma}{1-\gamma}\right]^{1-\alpha}\left[(p_A\theta_A)^{\frac{1}{1-\alpha}} + \alpha\,(p_M\theta_M)^{\frac{1}{1-\alpha}}\right]^{1-\alpha}. \tag{4}$$

From the result on employment and prices, it can be easily shown that agricultural productivity also has opposite effects on the production and profitability of the tradable and non-tradable sector. Specifically, $\frac{\partial y_M}{\partial \theta_A} < 0$ and $\frac{\partial \pi_M}{\partial \theta_A} < 0$ for the tradable sector, and $\frac{\partial y_S}{\partial \theta_A} > 0$ and $\frac{\partial \pi_S}{\partial \theta_A} > 0$ for the non-tradable sector.

Intuitively, Prediction 3 follows from the fact that a positive shock to productivity in the agricultural sector has two effects on local firms. On the one hand, it induces an increase in the cost of labor because increased demand for labor in agriculture causes the equilibrium wage to raise. On the other hand, the productivity shock positively affects local incomes and thus potentially the demand that firms face. For firms that produce locally but sell outside the district (tradable firms), demand is exogenous to local conditions, so only the first effect applies. It follows that a positive shock to agricultural productivity means lower profits, and thus reduced employment and production. For firms producing and selling locally (non-tradable firms), instead, a positive shock to agriculture implies an increase in the cost of labor but also an increase in demand (and thus price). The prediction illustrates how, under the model assumptions, the latter effect dominates, and so non-tradable production, employment and profits increase.

Prediction 4. A positive shock to agricultural productivity θ_A increases local income, I, and local consumption of all goods: $\frac{\partial I}{\partial \theta_A} > 0$ and $\frac{\partial c_j}{\partial \theta_A} > 0$ for $j \in \{A, M, S\}$.

The increase in income follows from the fact that $I = \pi_A + \pi_S + w$ and all its components are increasing in agricultural productivity. The increase in consumption of agricultural and traded goods is a direct consequence of the fact that income increases and prices of these goods are exogenous to local conditions. The increase in consumption of non-traded goods is a result of the fact that price p_S increases more than wage w. Further, this prediction is equivalent to $\frac{\partial y_S}{\partial \theta_A} > 0$ because in equilibrium $c_S = Y_S$.

2.2 The Introduction of a Rural Workfare Program

NREGA entitles every household in rural India to 100 days of public work per year at a state-level minimum wage. I introduce NREGA in the model as an employer that posts jobs at a fixed wage w^N.

Prediction 5. The availability of NREGA jobs induces a wage floor. That is, $w \geq w^N$ for any θ_A.

After NREGA is introduced, the local equilibrium wage cannot fall below the NREGA wage w^N. This is the case even when agricultural productivity realizations are very low. The introduction of NREGA induces a threshold $\bar{\theta}_A^N$ such that the pre-NREGA equilibrium wage emerges for any $\theta_A > \bar{\theta}_A^N$, while the equilibrium wage is equal to the NREGA wage w^N for any $\theta_A \leq \bar{\theta}_A^N$ [8]. This happens because for no agent it can be optimal to work for a wage lower than w^N when a NREGA job, which pays w^N, is available. This implies that if other employers in the local economy want to hire workers, they must pay at least the NREGA wage.

I am assuming here that NREGA labor demand at w^N is infinite, while we know that the implementation of NREGA limits employment to a maximum of 100 days. This is done to simplify the comparative statics. The key result that NREGA induces an increase in equilibrium wage for certain agricultural productivity realizations would still remain if I assumed that NREGA offered jobs up to a maximum amount $\overline{n}^N$. This alternative assumption would not deliver the wage floor prediction, but would still deliver a wage increase prediction, which is what matters for the results below.

Prediction 6. NREGA acts as a counter-cyclical stimulus policy. That is, the share of agents working for NREGA is decreasing in θ_A: $\frac{\partial n_N}{\partial \theta_A} < 0$.

Before the introduction of NREGA, the labor market clears through the equilibrium wage. After the introduction of NREGA, since the wage level is fixed at w^N, the labor market clears through the number of agents working for NREGA, n^N. That is, the new market clearing condition is given by:

$$n_N + n_A(w^N) + n_M(w^N) + n_S(w^N) = 1.$$

Now notice that, after the introduction of NREGA, labor demand in the tradable sector does not depend on θ_A (this happens because θ_A does not affect the equilibrium wage anymore, and so has no impact on the cost of labor that tradable firms face). Labor demand in the agricultural and non-tradable sector, instead, still positively depends on θ_A. It follows that labor market clearing requires NREGA employment to increase when agricultural productivity in the local economy is low. Prediction 7 implies that, empirically, we should observe NREGA take-up to increase during "bad times".

These considerations lead to Prediction 7, which illustrates the key implications of NREGA for the volatility that the local economy faces. Let ϵ_{y,θ_A} indicate the elasticity of

[8] For simplicity, I work below under the assumption that all agricultural productivity realizations are below the threshold $\bar{\theta}_A^N$. The full characterization would take into consideration the fact that, for good productivity realizations, the post-NREGA equilibrium is equivalent to the pre-NREGA equilibrium.

y with respect to θ_A before the introduction of NREGA, and let ϵ^N_{y,θ_A} indicate the same elasticity after the introduction of NREGA.

Prediction 7. NREGA acts as a local stabilizer. Specifically, NREGA:

- *Attenuates local wage elasticity:* $\epsilon^N_{w,\theta_A} < \epsilon_{w,\theta_A}$
- *Attenuates local income and consumption elasticity:* $\epsilon^N_{I,\theta_A} < \epsilon_{I,\theta_A}$ *and* $\epsilon^N_{c_j,\theta_A} < \epsilon_{c_j\theta_A}$ *for* $j \in \{A, M, S\}$.
- *Attenuates the counter-cyclical reallocation to the local non-farm tradable sector:* $\mid \epsilon^N_{n_M,\theta_A} \mid < \mid \epsilon_{n_M,\theta_A} \mid$
- *Attenuates the pro-cyclical reallocation to the local non-farm non-tradable sector:* $\epsilon^N_{n_S,\theta_A} < \epsilon_{n_S,\theta_A}$

Because of its stabilization effect on local wage, NREGA has an impact on local industrial volatility, and attenuates the short-term fluctuations in employment and production in the non-farm sector. Consider firms selling tradable goods first. When a negative shock hits the economy, NREGA prevents the wage to fall and thus prevents a reduction in the cost of labor that these firms face. As a consequence, these firms will increase their production and employment by less than they did pre-NREGA. Consider now firms selling non-tradable goods. When a negative shock hits the economy, NREGA, by preventing a wage decrease, also prevents a decrease in local incomes and thus in the demand that these firms face. Prediction 7 states that, given the model assumptions, the demand effect prevails and so non-tradable firms will decrease their production and employment by less than they did pre-NREGA. In sum, NREGA attenuates the volatility in local firm production and employment.

While I focus here on the implications of NREGA for local volatility, NREGA has effects on the level of local economic activity as well. In particular, NREGA also causes an increase in the wage level. This translates into an increase in the cost of labor and hence a reduction in profits for firms in the tradable sector. In turn, the reduction in profits will cause tradable firms to shrink. On the other hand, because of its positive effects on local demand, NREGA may induce higher production of firms in the non-tradable sector, thus fostering the development of the local non-farm non-tradable sector. The empirical analysis also examines these additional effects.

3 Data

This paper combines data from a large number of sources to provide a full picture of the effects of agricultural productivity on the local economy and to assess the impact of NREGA on local economic activity. It relies on a unique combination of district-level measures and micro-data for both firms and households.

3.1 Firm Data

The key dataset for firms is the Annual Survey of Industries (ASI), collected by the Ministry of Statistics and Program Implementation (MoSPI), Government of India. The ASI includes all registered manufacturing plants in India with more than fifty workers (one hundred if they operate without power) and a random one-third sample of registered plants with more than ten workers (twenty if without power). Sampling weights are provided so that the weighted sample reflects the population. I use sampling weights throughout the empirical analysis.

The ASI has extremely rich information on plant characteristics over the fiscal year (April of a given year through March of the following year) for around 50,000 plants each year. It collects information in balance-sheet format for a large number variables of interest (e.g. profits, output, number of employees, capital) so that it is possible to analyze how firms respond to agricultural productivity across multiple dimensions.

This paper uses 10 waves of data, spanning the fiscal years 2000-2001 to 2009-2010[9]. This sample includes years before the introduction of NREGA, to estimate the relevant elasticity in the absence of the policy, and years after the policy, to test whether NREGA caused a reduction in volatility. Importantly, the availability of yearly data allows me to analyze the exact timing of change in elasticities, and thus to verify that it tracks closely the timing of the implementation of NREGA across districts.

The key outcome variables considered are measures of production and employment. Production is measured using the value of total output. For employment, I use the total number of workers and total number of man-days employed. In some of the specifications, I distinguish blue-collar and white-collar workers, as well as permanent and contract workers. I also consider measures of profitability (gross value added and profits) and capital (total value of fixed capital). Finally, I construct a measure of daily wage dividing

[9]Additional waves are available after 2009-2010, but 2009-2010 is the last wave in which information on firm location at district-level is disclosed. In subsequent waves, location information is only available at the state-level. With no district information, it is not possible to match firm data to district measures. It is thus not possible to include later waves in the current analysis.

total compensation paid to workers by the number of man-days.

The ASI data collect information on industry up to 4-digit of the Indian National Industrial Classification (NIC). Industry classifications changed across the time span considered (from NIC 1998, to NIC 2004, to NIC 2008). I develop and apply a concordance across industrial classifications to be able to group firms into industries in a consistent way across years.

As illustrated in the model, agricultural productivity shocks have different effects on firms depending on the the type of goods they produce (traded vs. non-traded). I therefore require a criterion to classify firms according to the tradability of their products. I classify industries as tradable or non-tradable using three different definitions.

The first definition relies on a measure of industry tradability derived from the United States Census Commodity Flow Survey (CFS) in Holmes and Stevens (2014). Using the CFS, Holmes and Stevens (2014) calculate a measure of transportation costs for each 4-digit SIC industry which is closely correlated with average product shipment distance. According to this classification, industries that produce goods such as ice-creams, newspapers, bricks and cardboard boxes are among the least tradable, while those that produce watches, x-ray equipment and aircraft parts are the most tradable. I match U.S. 4-digit SIC codes to India 4-digit NIC codes and define an industry as tradable if the eta parameter in Holmens and Steven (2014) is less than 0.47. By this definition, 33 percent of the 4-digit manufacturing industries are tradable. Table 4 reports the list of 2-digit industries and, for each industry, indicates the share of industry output that is classified as tradable.

The second and third definitions of tradability rely on Kothari (2014), which in turn builds on the classifications of tradable industries used in Mian and Sufi (2014). Kothari (2014) constructs two measures of tradability at the 3-digit NIC level. The first is based on a measure of geographical concentration of industrial production across counties in the United States. Industries whose production is highly concentrated in a few counties in the U.S. are considered to be tradable, while industries that have production spread over lots of counties are considered non-tradable. I apply this measure of industry tradability based on U.S. levels of concentration to India. The second measure in Kothari (2014) is based on the degree of international trade carried out in any Indian industry as a share of domestic production. Industries in which international trade is a large percent of domestic production are considered to be more tradable. These definitions distinguish industries that are below/above median tradability, and hence classify 50 percent of the 3-digit manufacturing industries are tradable.

I also derive a classification of industry linkages to the agricultural sector. I classify 4-digit NIC industries as upstream or downstream of agriculture using the India MOSPI Input-Output tables for 2004-2005. For each industry, I calculate the agriculture output share, that is, the share of industry output that is purchased by the agricultural sector. I define an industry as "upstream" of agriculture if this upstream linkage share is larger than 3 percent. I then calculate the industry agriculture input cost share, that is, the share of industry input that is purchased from the agricultural sector. An industry is "downstream" if the agriculture input cost share is larger than 20 percent. I refer to an industry as "non-linked" if it is neither upstream nor downstream. By this definition, 2 percent of firms in the ASI data are upstream and 17 percent are downstream. The most-linked upstream industries include those that produce fertilizers, pesticides and other agrochemical products, while the most-linked downstream industries include many that process agricultural output and manufacture food.

Using ASI 2000-2001, I also define a measure of capital intensity. For each firm, I compute the ratio between fixed assets and total compensation paid to employees. I then compute an average of this measure at the industry level and define an industry as capital intensive if the industry measure if above the median across industries.

Finally, I define a measure of industry dependence on external finance. I compute the ratio between outstanding loans and fixed assets. This is in the spirit of Rajan and Zingales (1998). A higher ratio indicates that a higher share of capital is financed through external funds. I define an industry as highly dependent on external finance if the industry average is above the median across industries.

Table 1 reports summary statistics for all firms in the ASI data. Tables 2 and 3 provide summary statistics distinguishing firms by industry type (tradable vs. non-tradable) and by NREGA-implementation-phase.

3.2 Consumption Data

Consumption expenditure measures come from the National Sample Survey (NSS) Consumer Expenditure Survey (Schedule 1). I use 7 waves spanning the years 2003-2004 to 2011-2012. Specifically, the analysis includes the NSS waves 60, 61, 62, 63, 64, 66 and 68.

The survey includes extremely detailed information on consumption expenditure, collecting information on more than 400 consumption items. In the empirical analysis, I focus on monthly per capita expenditure (MPCE). This is computed as total monthly expenditure divided by household size. I consider both total MPCE and MPCE in different consumption categories. In particular, I group items into the three categories of food consumption, manufactured goods consumption, and services consumption.

I define real consumption dividing nominal consumption by the state Consumer Price Index for Agricultural Labourers, published by the Government of India.

3.3 Wages and Employment Data

Wage and employment data are from the NSS Employment and Unemployment Survey (Schedule 10). The data include 6 waves spanning the years 2003-2004 to 2011-2012. Specifically, the analysis includes the NSS waves 60, 61, 62, 64, 66 and 68.

The NSS asks individuals who worked for a wage their total earnings in the 7 days preceding the survey. I construct a measure of daily wage dividing total earnings by the number of days worked. The NSS survey provides information on the industry in which the individual works, so I can define an overall district wage, and, separately, an agricultural and a non-agricultural district wage. The survey also allows to distinguish workers in regular or casual wage work. The survey covers a rich set of demographic characteristics, including age, gender, education and landholdings. This allows to include in the wage and employment specifications worker-level controls. This guarantees that the estimates capture actual impacts of agricultural shocks and not just changes in the composition of workers.

The NSS collects information on employment in the 7 days before the survey. I compute the number of days that an individual spends in the labor force, unemployed or working in different sectors.

3.4 Agricultural Data

I use data on annual district level agricultural production collected and published by the Directorate of Economics and Statistics, Ministry of Agriculture. This data is reported at the financial year level, which ranges from April to March in the subsequent calendar year. For every district, I only consider crops that have been consistently planted on at least 1,000 hectares during all the years in which the data are available. The resulting dataset is an unbalanced panel dataset covering the period from 2000-2010.

For a given crop, the yield is computed as total production divided by area cultivated. I construct a yearly measure of district agricultural yield computing the weighted average of the yields of the different crops consistently cultivated in the district, with area cultivated under a given crop used as weight.

Additional agricultural data, such as district-level measures of total area cropped and area irrigated, are from the Land Use Statistics Information System, Indian Ministry of Agriculture.

3.5 Rainfall Data

This paper uses data from the Tropical Rainfall Measuring Mission (TRMM), developed by the National Aeronautics and Space Administration (NASA) and the Japan Aerospace and Exploration Agency (JAXA). The TRMM provides gridded rainfall rates at very high spatial and temporal resolution. Daily rainfall measures are available at the 0.25 by 0.25 degree grid-cell size, and are converted into overall monthly rainfall measures. Rainfall in a given district-year refers to rainfall registered on the grid point closest to the district centroid. For the empirical analysis, I focus on total monsoon rainfall, which I define as total rainfall in the months of June, July, August and September. In the Indian context, monsoon rainfall accounts for at least 70% of annual rainfall.

I also define a categorical variable aimed at capturing possible non-linearities in the effects of rainfall. The variable Rainfall Shock equals one if monsoon rainfall is greater than the district's eightieth percentile of monsoon rainfall, zero if between the twentieth and eightieth percentiles, and minus one if below the twentieth percentile. This is the same measure used in Jayachandran (2006). I also show that results are robust to a continuos measure of rainfall deviation from its average, and compute the yearly fractional deviation from the long-run district's mean monsoon rainfall.

3.6 NREGA Data

Data on participation to NREGA come from the NSS Employment and Unemployment Survey, waves 64, 66 and 68. I compute the number of days in the reference week that an individual spends working under NREGA. Participation figures from household surveys are likely more reliable than participation figures available from administrative sources, and so are preferred to those.

The NSS Survey also asks information on the total earnings received from wage work under NREGA. Dividing total earnings by the number of days worked, I obtain a measure of the NREGA wage that a worker receives. These wages are used to compute the district average wage paid under NREGA in a given year. These wages are then compared to the state-specific NREGA statutory wages, which vary over time. To make the comparison possible, I complied information on NREGA statutory wages using multiple administrative sources, including the notifications of NREGA wage revisions available in the Gazette of India. Figures 6 and 7 provide an illustration of the cross-section and over time variation in the NREGA statutory wage and its relation to the actual wage being paid under the program.

4 Background

The National Rural Employment Guarantee Scheme was introduced in India in 2005 through the National Rural Employment Guarantee Act. The Act entitles every rural household to 100 days of public-sector work a year at a minimum wage established at the state-level. According to government administrative data, in 2010-2011 the NREGA provided 2.27 billion person-days of employment to 53 million households, with a budget that represents 0.6% of Indian GDP. The size of the program makes it one of the largest and most ambitious public-works employment schemes ever attempted worldwide.

The type of work generated by the program is low-wage, casual, unskilled manual work, often in construction and for projects in transport infrastructure, irrigation or water conservation. Employment creation and poverty reduction are at the core of the program, and this is apparent in a number of the Act provisions, including those that govern project costs. The Act limits material, capital and skilled wages expenditures to 40% of total expenditures, thus reserving the remaining 60% to expenditure on unskilled wages. The Act also establishes that the central government bears the entire cost of unskilled manual workers, but only 75% of the cost of material, capital and skilled workers, with the state government responsible for the remaining 25%. This creates an incentive for states to select projects that are intensive in unskilled-labor and is meant to induce large employment creation per unit of budget.

Participation in NREGA does not entail formal requirements, and any individual can participate to the program as long as he resides in rural areas and is willing to earn at the minimum wage and performing manual work. NREGA hence relies on self-selection of individuals into the workfare program. Both women and men can participate to the program, and the Act in fact explicitly states that female workforce must be involved in at least one third of the work created, and that men and women must receive the same wage. The importance of these provisions from a gender perspective and their implications on women empowerment and female labor force participation have been the object of some of the studies that have documented the introduction of NREGA (Afridi et al., 2012; Azam, 2012; Dreze and Khera, 2009).

Households can apply for work at any time of the year. The application process as established in the Act entails a few steps. Households first apply for a job card which is issued by the local Gram Panchayat. Once in posses of the job card, households can submit an application to the Gram Panchayat, stating the time and duration for which they seek employment. The Act mandates that, following such a request, employment on a public-works project is to be provided within 15 days of the application. If this statutory 15 day deadline is exceeded, the household is entitled to a daily unemployment allowance. The program was therefore designed to be demand-driven and highly responsive to the needs of rural households, though some studies and field reports have documented substantial variation in the implementation standards across states and districts (Dreze and Khera, 2009; Dutta et al., 2012; Niehaus and Sukhtankar, 2012 and 2013; Papp, 2012; Sharma, 2009; World Bank, 2011).

NREGA was rolled out in rural India in three phases, between 2006 and 2008. The first phase started in the first quarter of 2006, when the program was implemented in 200 districts. In 2007, 130 further districts were added. In 2008, the third phase included the remaining districts into the scheme. NREGA currently covers all Indian districts except a few entirely urban centers. Districts that received NREGA in the earlier phases were selected to have lower agricultural wages and lower agricultural output per worker, though this criterion was combined with the objective of starting the program in all states. This caused a number of districts in richer states to receive the program early. As a consequence, some early phases districts in richer states were in fact significantly better across a number of economic indicators than late phase districts in poorer states.

5 Empirical Strategy

The empirical analysis uses the predictions derived in Section 2 to study the effects of agricultural productivity fluctuations on the local economy and to test whether NREGA had an impact on how such fluctuations get transmitted through the local economy. Hence, it has two parts.

In the first part, I study the relationships between farm and non-farm sector for the years before NREGA is introduced. In the second part, I show how the introduction of NREGA changes the way in which the local economy responds to shocks.

The first part exploits exogenous variation in agricultural productivity due to monsoon rainfall realizations across districts and over time to estimate the elasticity of equilibrium outcomes with respect to rainfall. The second part takes advantage of the timing in NREGA implementation to test for a change in the elasticities as predicted by the model.

5.1 The Effect of Agricultural Productivity on the Local Non-Farm Sector

I estimate the relationship between rainfall and local outcomes using the time period prior to the introduction of NREGA. This guarantees that the estimates are not affected by any impact that NREGA may have. To establish the impact of rainfall on the local economy, I provide evidence for each channel of the transmission mechanism. First, I test the key idea that rainfall affects agricultural productivity, by providing estimates of the elasticity of district crop yield to rainfall. Then, I estimate the impact of NREGA on (i) local wages, (ii) local consumption, (iii) local firm production and employment.

First, I analyze the effect of rainfall on district crop yields. I focus on monsoon rainfall (June to September) since this is the most important for India's agricultural productivity. I estimate the following equation:

$$log(y_{dpt}) = \beta log(R_{dpt}) + \delta_d + \tau_{pt} + \varepsilon_{dpt} \tag{5}$$

where d stands for district; p stands for NREGA implementation-phase, ranging from 1 to 3; and t indicates time. The regression includes two sets of fixed effects. First, district fixed effects, which capture any time-invariant district characteristics that affects the level of agricultural productivity. The second are time fixed effects. The time fixed effects are NREGA-implementation-phase specific, and thus remove yearly shocks that are common to the districts which received NREGA in phases 1, 2 or 3[10].

The coefficient of interest is β. The prediction is that monsoon rainfall strongly affects agricultural production. I expect this to be the case since in India more than 50% of agriculture is rainfed and so highly dependent on the monsoon realization for irrigation.

In this and all regressions below, standard errors are clustered at the district level to capture serial correlation. Results are virtually unaffected if instead I cluster standard errors at the region-year level to allow for spatial correlation.

Second, I establish the impact of monsoon rainfall on wages through the regression:

$$log(w_{idpt}) = \beta log(R_{dpt}) + \rho X_{idpt} + \delta_d + \tau_{pt} + \varepsilon_{idpt} \tag{6}$$

where i indexes an individual. Fixed effects are as above. The regression includes worker's demographic characteristics, X_{idpt}, to tackle the possibility that composition

[10] I could alternatively introduce time fixed effects common across districts, and indeed results are unchanged in such case. NREGA-implementation-phase specific fixed effects are introduced mainly to keep the pre-NREGA specifications consistent with the specifications that estimate the impact of NREGA.

changes. For robustness, I also estimate specifications that add state-specific time trends, or trends on initial district conditions (that is, time trends interacted with time-invariant district characteristics such as poverty rate), to allow wages to trend differently across different districts. I run the regression on all wages, as well as separately for high-skilled/low-skilled and agricultural/non-agricultural workers.

Third, I estimate the elasticity of local consumption. The specification is the same as the one used for wage elasticity, except that the unit of observation is a household rather than a worker. I estimate the elasticity of monthly per capita expenditure using both total consumption and different consumption components (specifically, food consumption, manufactured goods consumption and services consumption).

Fourth, I analyze the impact on rainfall on firm outcomes. The estimating equation is:

$$log(y_{jdpt}) = \beta log(R_{dpt}) + \delta_d + \tau_{pt} + \vartheta_{pj} + \rho_{jt} + \varepsilon_{jdst} \tag{7}$$

which studies outcome y for firms in industry j operating in district d of NREGA implementation-phase p at time t.

District and time fixed effects are as in the specifications above. NREGA-implementation-phase specific industry fixed effects are included to capture time-invariant industry characteristics that are common within a NREGA implementation phase. I also include industry-specific time fixed effects to allow industries to grow at different rates over time.

The coefficient of interest is β. The main hypothesis is that, before the introduction of NREGA, there was a significant link between monsoon rainfall and manufacturing production and employment.

The model in Section 2 illustrates how we should expect the impact of rainfall to differ depending on whether a firm produces traded or non-traded goods. To capture this, I estimate the regression separately for tradable and non-tradable sectors using a dummy T_j that captures tradability of a given industry. For robustness, I use multiple tradability definitions. The data section reports information on how these dummies are constructed.

5.2 The Introduction of a Rural Workfare Program

The second part of the empirical analysis tests whether the introduction of NREGA caused an attenuation of the relationships above. This is done using the empirical setup presented above and adding an interaction term to those specifications. That is, I include the interaction between rainfall and an indicator N_{dpt} which is equal to 1 if district d in implementation phase p has NREGA at time t.

The identifying assumption in this part is that the timing of the implementation of NREGA across-districts is not correlated with any omitted variable that may also attenuate the rainfall-dependence of the local economy. It is important to note that this identifying assumption does not require the timing to be uncorrelated with trends in the outcome variables of interest. Indeed, the inclusion in the specification of time fixed effects that are specific to each NREGA implementation phase implies that identification is coming off of districts within the same implementation phase. That is, the specification flexibly allows for the possibility that different implementation phases are on different trends.

In this part, I first show that NREGA has the potential to attenuate local volatility because NREGA jobs provision increases when the local economy is hit by a negative agricultural productivity shock. I then proceed by studying the moderating effect of NREGA on local outcomes following the same order of the specifications above.

First, I provide evidence that NREGA take-up responds to rainfall using the regression:

$$log(y_{idpt}) = \beta log(R_{dpt}) + \gamma log(R_{dpt}) \times N_{dpt} + \rho X_{idpt} + \delta_d + \tau_{pt} + \varepsilon_{idpt} \tag{8}$$

where y represents the time that individual i spends working in public works. Other indexes are as in the specifications above. The prediction is that $\beta = 0$ and $\gamma < 0$. That is, before the introduction of NREGA, there was no relation between public employment and rainfall. Once NREGA is introduced, individuals respond to a negative productivity shock resorting to NREGA jobs, and do so to a larger extent the worse is the shock.

Second, I show that, at least in the time period considered, NREGA did not attenuate the relationship between rainfall and agricultural yields. It is possible that in the long-run NREGA makes agricultural yields less sensitive to rainfall, for instance through an impact on irrigation infrastructure. However, I show that this does not seem to be happening in the years right after its introduction. This means that any attenuation in the response of a given variable to rainfall (the reduced form) can be interpreted as the result of an attenuation in the response of such variable to agricultural yields (the second stage), rather than an attenuation in the response of agricultural yields to rainfall (the first stage).

Third, I show the moderating impact of NREGA on wage elasticity. The specification for wage elasticity becomes as follows:

$$log(w_{idpt}) = \beta log(R_{dpt}) + \gamma log(R_{dpt}) \times N_{dpt} + \rho X_{idpt} + \delta_d + \tau_{pt} + \varepsilon_{idpt} \tag{9}$$

Notice that the treatment dummy N_{dpt} is collinear to the NREGA-implementation-phase-specific time fixed effects. Hence, the specification does not estimate the impact that NREGA has on the level of the outcome variable. It instead tests whether the way in which rainfall translates into local wages changes with the availability of NREGA jobs. The prediction is that $\beta > 0$ and $\gamma < 0$, that is, NREGA reduces local wage volatility.

The same specification is used to assess the effect of the introduction of NREGA on consumption volatility.

Finally, I test whether NREGA had a moderating impact on local industrial production and employment. The specification for firm outcomes becomes:

$$log(y_{jdpt}) = \beta log(R_{dpt}) + \gamma log(R_{dpt}) \times N_{dpt} + \delta_d + \tau_{pt} + \vartheta_{pj} + \rho_{jt} + \varepsilon_{jdst} \qquad (10)$$

One concern with the specifications above is that the NREGA treatment may be capturing a more general over-time decline in the rainfall-dependence of the local economy, or the impact of other contemporaneous policies that affect rainfall-dependence. I tackle this possibility by estimating, for each of the outcomes above, a yearly measure of elasticity. This allows me to track elasticities throughout the study time period and show that the timing of the elasticity attenuation coincides with the introduction of NREGA across the three implementation phases. Specifically, I estimate a regression that includes the term $\sum_{s\in\{-7,-6,\ldots,2,3\}} \beta_s log(R_{ds})$. The aim is to plot the estimated coefficients β_s together with their confidence intervals, and show that the pattern is such that the β_s are mostly constant in the period before NREGA, jump in correspondence of the introduction of NREGA and stabilize at the new level in the subsequent years.

6 Results

The results, as the empirical strategy, comprise two parts. In the first part, I estimate the relationships between rainfall and local outcomes in the period before the introduction of NREGA. In the second part, I present the results that consider the entire period and show how the introduction of NREGA affects such relationships.

6.1 The Effect of Agricultural Productivity on the Local Non-Farm Sector

I start by establishing that monsoon rainfall has an impact on agricultural productivity in the time period considered in this study. Table 5 shows that monsoon rainfall has a large effect on district crop yields, and illustrates how the effect changes with the share of cultivated land that is irrigated.

I then estimate the impact of monsoon rainfall on local wages. Table 6 reports the results. Consistently with the hypothesis of local labor mobility across sectors, the estimates show that rainfall affects not only the wage in the agricultural sector but also the wage in the non-agricultural sector.

Table 7 presents the estimates of consumption elasticity. The consumption regressions test the prediction that rainfall is an important driver of demand in the local economy. The results show that there is a strong relationship between rainfall and monthly per capita expenditure. Columns (2) and (3) distinguish food and non-food consumption. They show that the impact is weakest on food consumption and strongest on non-food. Column (4) reports the elasticity for consumption expenditure on manufactured goods. This is the estimate most closely related to the effect that a rainfall shock has on the demand for the goods that manufacturing firms produce.

Estimates of the response of local firms to agricultural fluctuations are presented in Table 8. Consistently with the evidence in Table 6, Column (4) shows that a positive rainfall realization raises the cost of labor for local manufacturing firms. However, even though they face higher labor costs, firms respond pro-cyclically to shocks to agricultural productivity. The estimates of production and employment elasticities in Columns (1) to (3) are indeed positive. The results suggest that the (positive) local demand effect more than compensate the (negative) local wage effect that results from a positive realization of monsoon rainfall.

Evidence in support of the demand channel is presented in Table 9. The table reports the results from regressions that consider separately firms in tradable and non-tradable industries. The estimates show that pro-cyclicality is driven by firms that produce non-tradable goods. For firms that produce tradable goods, instead, the estimated elasticities are negative, even though not significant. These estimates are consistent with the model prediction of opposite effects on firms that sell traded vs. non-traded goods.

6.2 The Introduction of a Rural Workfare Program

In this part I test the hypothesis that the introduction of NREGA led to a moderation of the relationships between rainfall and local outcomes.

The stabilization potential of NREGA rests on the fact that NREGA jobs provision increases when the local economy is hit by a negative agricultural productivity shock. I therefore test whether local participation to NREGA increases when there is a negative rainfall realization. Results are reported in Column (2) of Table 10. The estimates confirm that, pre-NREGA, participation in public employment was not linked to rainfall. Once NREGA is introduced, instead, take-up of public works jobs is significantly (negatively) correlated to rainfall.

Column (1) of Table 10 shows that, in the time period considered, NREGA did not attenuate the relationship between rainfall and agricultural yields. This means that any attenuation in the response of a given variable to rainfall (the reduced form) can be interpreted as the result of the attenuation in the response of such variable to agricultural yields (the second stage), rather than an attenuation in the response of agricultural yields to rainfall (the first stage).

Table 11 tests the prediction that the introduction of NREGA attenuated local wage volatility. The results support the hypothesis that NREGA stabilized the wage, and in fact suggest that NREGA brought the wage elasticity to zero.

That NREGA has a moderation effect on local volatility also emerges from Table 12, that reports the results for local consumption. The introduction of NREGA attenuated the relationship between rainfall and consumption. This means that NREGA is able to support local demand when agricultural productivity, and therefore incomes, are low.

Table 13 and 14 test the hypothesis that NREGA affects the way in which local firms respond to agricultural fluctuations. Results are reported separately for the different NREGA implementation phases, since they differ in their pre-NREGA volatility, and, as a consequence, in the potential attenuation post-NREGA. The results are consistent with the hypothesis that NREGA attenuated the pro-cyclical response of non-tradable firms in Phase 1 and 2 districts. Post-NREGA, production and employment fluctuate to a lesser extent in response to agricultural fluctuations.

6.3 Robustness Checks

In this section I perform a number of robustness checks to show that the estimates are robust to deviations from the baseline framework.

First, I show the robustness of the results to alternative ways of measuring the weather shock. Table 15 reports the results of estimating firm elasticities using a measure of rainfall shock instead of total rainfall. The variable Rainfall Shock equals one if monsoon rainfall is greater than the district's eightieth percentile of monsoon rainfall, zero if between the twentieth and eightieth percentiles, and minus one if below the twentieth percentile. This is the same measure used in Jayachandran (2006). I also define the variable Rainfall Deviation which is equal to the yearly fractional deviation from the long-run district's mean monsoon rainfall. The results obtained using these measures are very similar to the baseline results and are statistically significant.

Second, I show that the heterogenous impact across tradable and non-tradable industries is robust to alternative tradability classifications. Panel A in Table 16 reports the estimates of firm elasticities separately for tradable and non-tradable industries using the classification based on geographical concentration. Panel B reports the elasticities estimated using the classification based on international trade. The results confirm that the pro-cyclical response in driven by firms in non-tradable industries.

In a third set of robustness checks, I tackle the possibility that yearly fluctuations in rainfall could potentially have an impact on the non-agricultural sector through channels other than agricultural productivity. I show results from two placebo tests. First, I exploit the fact that there is large variation across districts in access to irrigation sources. I identify poorly irrigated districts (those for which less than 20% of cultivated land is irrigated) and highly irrigated districts (those for which more than 60% of cultivated land is irrigated). Each group accounts for around 30% of Indian districts. Access to irrigation makes agriculture less susceptible to weather variation and hence we would expect crop yields in highly irrigated districts to be affected by monsoon rainfall very limitedly. Column 1 and 2 in Table 17 show that the first-stage effect of rainfall on agricultural productivity is strong only in districts with poor access to irrigation. Additionally, Columns 3 to 10 show that the reduced-form effect of rainfall on firm outcomes only exists in these same districts. The elasticities of firm wage, production and employment in highly irrigated districts are much smaller and not statistically significant. This lack of both first-stage and reduced-form effects in highly irrigated districts suggests that the effect of growing-season rainfall on firms operates through the key channel of agricultural productivity.

The second placebo check tests whether rainfall outside the main growing season has an effect on firms. The key idea is that rainfall outside the monsoon season should not be a strong determinant of agricultural productivity and hence should not have an impact on industrial outcomes. The results are presented in Table 18. Column 1 shows that non-monsoon rainfall has a very limited impact on district crop yields. Consistently with agricultural productivity being the key channel through which monsoon rainfall affects firms, Column 2 to 5 show that the elasticities of firm outcomes to non-monsoon rainfall are small in magnitude and not statistically significant.

The fourth robustness check assesses whether the findings reflect the strength of another channel through which agricultural productivity can affect the manufacturing sector:

input-output linkages. Farming requires inputs produced by other sectors, including manufacturing. This means that an increase in agricultural productivity in a given district might increase the demand for industries that produce inputs used in agriculture, such as chemicals or fertilizers. To the extent that manufacturing firms producing chemicals and fertilizers face high transport costs, their production and employment would respond to local demand conditions. Therefore, the effect of rainfall that I show could potentially be explained by an increase in the agricultural demand for manufacturing inputs. A similar argument applies to manufacturing industries that use agricultural goods as intermediate inputs – for instance, industries that process food. In order to assess the contribution of these direct linkages on my estimates, I use the Indian Input-Output table (2004-2005) to identify industries directly linked to agriculture through input-output linkages, either upstream or downstream. I then use this information to define non-linked industries and estimate elasticities for this subset. Table 19 reports the results from regressions that consider separately firms that are linked and non-linked to the agricultural sector, and, for the latter, shows results separately for firms in tradable and non-tradable industries. Column (1) reports the elasticity estimates for firms that are linked to agriculture. The estimates are indeed larger than for the overall sample. However, Columns (2) to (4) show that rainfall has a positive impact also on firms in non-linked non-tradable industries. Taken together, these results imply that the pro-cyclical response of the manufacturing sector is not fully driven by the processing of agricultural output in downstream industries or by larger agricultural sector demand for upstream industries.

Fifth, Table 20 shows that the results remain statistically significant when I correct standard errors to account for spatial correlation by clustering at the region-year level.

Finally, I provide evidence for the robustness of the results on the stabilization impact of NREGA. One concern with the baseline specification is that the NREGA treatment may be capturing a more general over-time decline in the rainfall-dependence of the local economy, or the impact of other contemporaneous policies that affect rainfall-dependence. I tackle this possibility by estimating yearly measures of elasticity. This allows me to track elasticities throughout the study time period and show that the timing of the change in elasticity coincides with the introduction of NREGA. Figures (1) to (3) plot the estimated elasticities together with the confidence interval. The coefficient patterns show that elasticities are relatively constant in the period before NREGA, and move to a different level in correspondence of the introduction of NREGA, thus reassuring against the hypothesis that NREGA is capturing the attenuation effect of other omitted variables.

7 Conclusion

How do agricultural productivity shocks propagate through the local economy and affect manufacturing firms? I present a simple model of a small open economy to illustrate how shocks to the farm-sector are transmitted to local firms through linkages in the labor and goods market. Using variation in weather realizations across districts and over time, I estimate the response of local firms' production and employment to agricultural productivity shocks, and show that firms respond pro-cyclically. The evidence best supports a local demand story: the higher incomes resulting from agriculture translate into higher demand for local non-tradable firms. The results highlight the importance of the mobility of goods for local volatility, and illustrate how local rural incomes continue to play an important role in determining the economic opportunities of manufacturing firms.

The paper additionally examines whether the introduction of a rural workfare program, the NREGA, affects the response of the local economy to agricultural volatility. It shows that the program acts as a stabilization policy and attenuates the pro-cyclical response of local wage, consumption, and firms' outcomes to agricultural productivity shocks. The evidence from NREGA exemplifies how policies not targeted to firms can still exert sizable influence on firms' decisions because of their impact on the economy in which both firms and farms operate. Attention in the past has focused only on policies that affect firms directly. This paper instead highlights how attention should also be paid to policies that target rural households and the agricultural sector, as these have far-reaching consequences.

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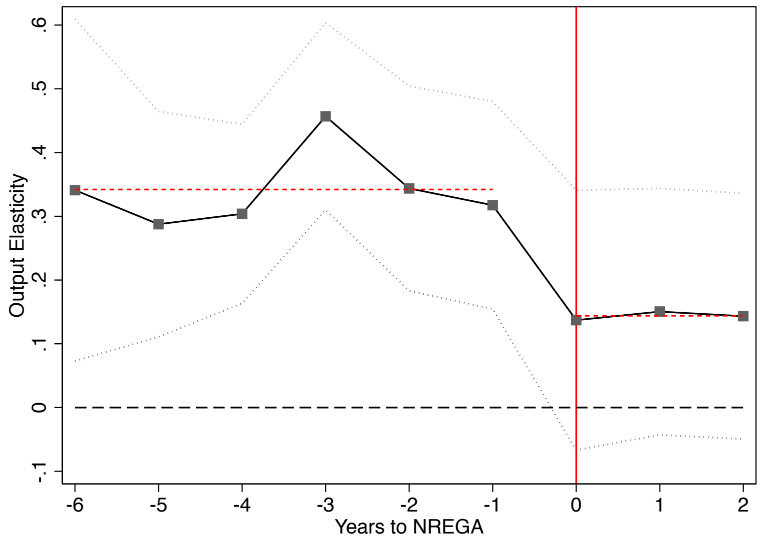
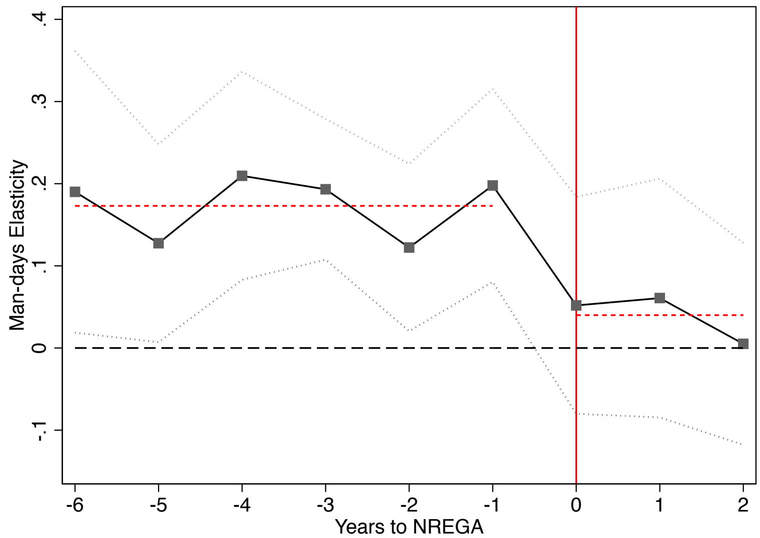
Figure 1: NREGA Phase 1 and 2 – Non-Tradable Output Elasticity Over Time



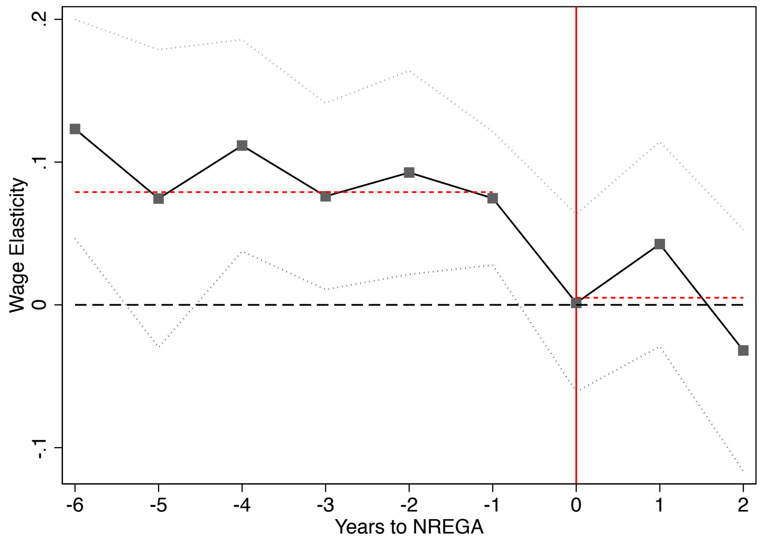
Notes: The vertical red line indicates the date of introduction of NREGA. The black line reports the estimated elasticity of manufacturing output with respect to monsoon rainfall for each year before and after the introduction of NREGA. The dotted black lines indicate the 90% confidence intervals. The red dashed lines report the coefficients obtained from the interaction of monsoon rainfall with the NREGA treatment dummy. Sample is restricted to NREGA-implementation Phases 1 and 2.

Figure 2: NREGA Phase 1 and 2 – Non-Tradable Employment Elasticity Over Time



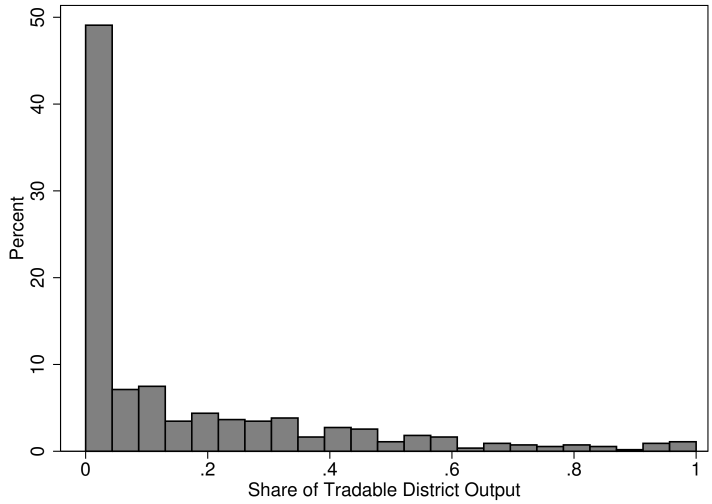
Notes: The vertical red line indicates the date of introduction of NREGA. The black line reports the estimated elasticity of manufacturing employment with respect to monsoon rainfall for each year before and after the introduction of NREGA. The dotted black lines indicate the 90% confidence intervals. The red dashed lines report the coefficients obtained from the interaction of monsoon rainfall with the NREGA treatment dummy. Sample is restricted to NREGA-implementation Phases 1 and 2.

Figure 3: NREGA Phase 1 and 2 – Wage Elasticity Over Time



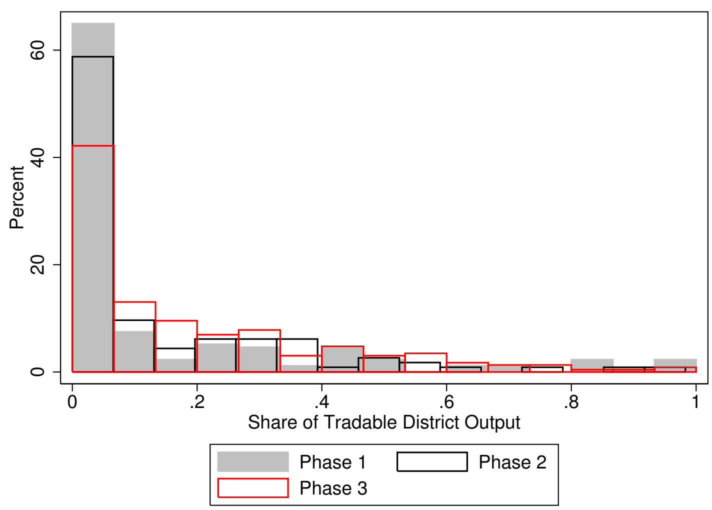
Notes: The vertical red line indicates the date of introduction of NREGA. The black line reports the estimated elasticity of manufacturing wage with respect to monsoon rainfall for each year before and after the introduction of NREGA. The dotted black lines indicate the 90% confidence intervals. The red dashed lines report the coefficients obtained from the interaction of monsoon rainfall with the NREGA treatment dummy. Sample is restricted to NREGA-implementation Phases 1 and 2.

Figure 4: Share of Tradable Output across Districts



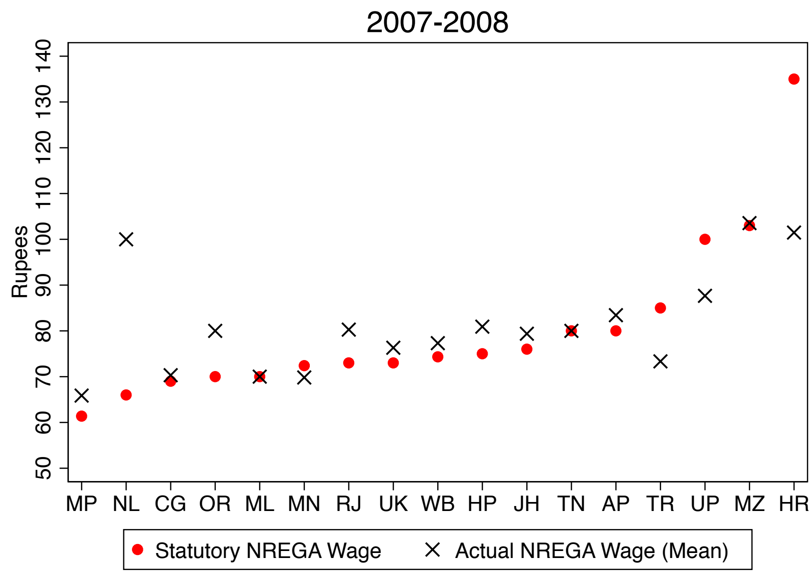
Notes: For each district, the share of tradable output is computed as total manufacturing output in industries classified as tradable divided by total district manufacturing output. The figure plots the distribution across Indian districts.

Figure 5: Share of Tradable Output across NREGA Phases



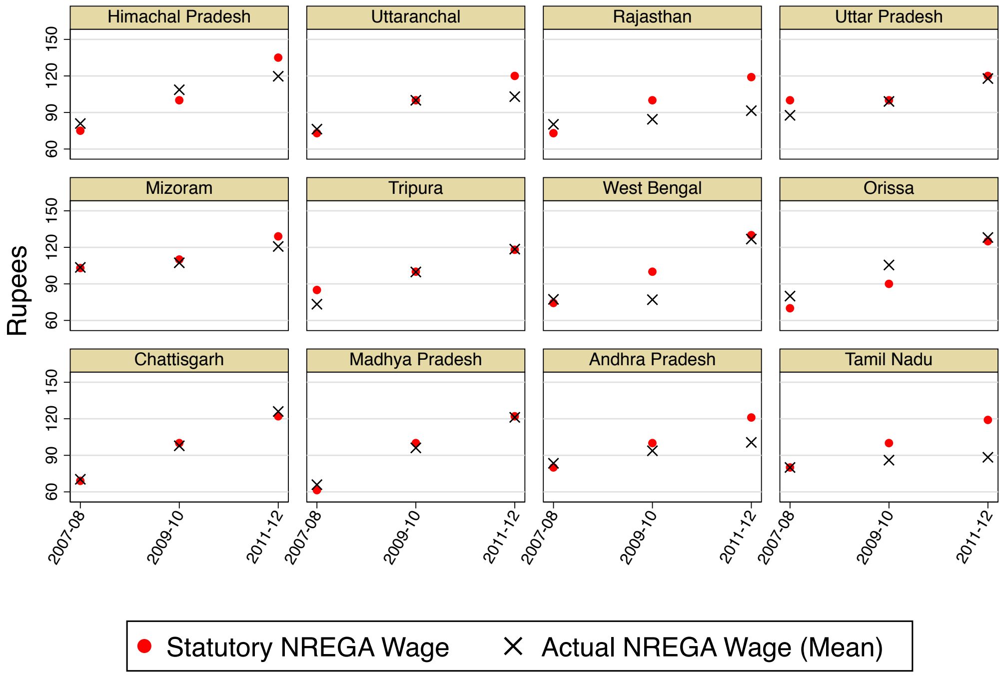
Notes: For each district, the share of tradable output is computed as total manufacturing output in industries classified as tradable divided by total district manufacturing output. The figure plots the distribution across Indian districts separately by NREGA-implementation-phase.

Figure 6: Cross-Section Variation in NREGA Statutory Wage



Notes: Actual NREGA mean daily wages for each state-year are computed using the NSS Employment and Unemployment Survey (Wave 64). For each NREGA worker, actual wage being paid is computed as total earnings in NREGA public work divided by the number of days in NREGA public work. NREGA statutory wages were assembled using multiple administrative sources, including the notifications of NREGA wage revisions available in the Gazette of India – see the Data Section for more details.

Figure 7: Over-Time Variation in NREGA Statutory Wage



Notes: Actual NREGA mean daily wages for each state-year are computed using the NSS Employment and Unemployment Survey (Waves 64, 66 and 68). For each NREGA worker, actual wage being paid is computed as total earnings in NREGA public work divided by the number of days in NREGA public work. NREGA statutory wages were assembled using multiple administrative sources, including the notifications of NREGA wage revisions available in the Gazette of India – see the Data Section for more details.

Table 1: ASI Summary Statistics

Characteristics	**Mean**	**Median**	**p10**	**p90**	**S.D.**
Number of Workers	68.47	23.00	7.00	144.00	155.87
Value of Output (Millions Rupees)	109.71	10.47	0.70	197.09	445.21
Fixed Capital (Millions Rupees)	36.24	2.03	0.15	48.22	178.01
Daily Wage (Rupees)	143.26	108.30	60.14	256.27	120.34
Output per Worker (Millions Rupees)	1.26	0.46	0.05	2.88	3.16
Capital to Labor Ratio	8.50	3.14	0.37	16.80	44.69

Notes: Sample refers to the years 2000-2001 to 2009-2010 and is restricted to rural areas. All estimates are obtained using sampling weights.

Table 2: ASI Summary Statistics by Industry Type

	All Industries	Non-tradable Industries	Tradable Industries
Number of Workers	68.47	60.04	99.31
	(155.9)	(138.2)	(205.2)
Value of Output (Millions Rupees)	109.7	98.68	150.1
	(445.2)	(426.0)	(507.4)
Fixed Capital (Millions Rupees)	36.24	31.67	52.90
	(178.0)	(171.3)	(199.8)
Daily Wage (Rupees)	143.3	135.9	170.7
	(120.3)	(113.5)	(139.4)
Output per Worker (Millions Rupees)	1.264	1.283	1.193
	(3.158)	(3.354)	(2.301)
Capital to Labor Ratio	8.496	8.621	8.034
	(44.69)	(49.24)	(20.51)

Notes: Sample refers to the years 2000-2001 to 2009-2010 and is restricted to rural areas. All estimates are obtained using sampling weights.

Table 3: ASI Summary Statistics by NREGA Phase

	All	**Phase 1**	**Phase 2**	**Phase 3**
	Panel A: All Industries			
Number of Workers	67.00	62.76	56.01	71.86
	(150.8)	(155.4)	(141.9)	(151.8)
Value of Output (Millions Rupees)	109.7	86.89	97.06	121.2
	(445.1)	(370.0)	(438.3)	(468.6)
Fixed Capital (Millions Rupees)	36.43	33.93	34.61	37.81
	(178.9)	(178.0)	(194.1)	(174.3)
Daily Wage (Rupees)	143.2	120.0	132.0	154.3
	(120.3)	(91.82)	(110.1)	(129.7)
Output per Worker (Millions Rupees)	1.268	1.059	1.168	1.368
	(3.162)	(2.091)	(2.714)	(3.555)
Capital to Labor Ratio	8.548	8.746	10.13	7.997
	(45.19)	(22.00)	(91.99)	(23.74)

Notes: Sample refers to the years 2000-2001 to 2009-2010 and is restricted to rural areas. All estimates are obtained using sampling weights.

Table 4: Tradable Industries

Industry Code	Industry Description	Tradable Industry Output / Total Industry Output	Industry Output / Total Output Across Industries
30	Office, Accounting and Computing Machinery	1.00	0.01
32	Radio, Television and Communication Equipment and Apparatus	1.00	0.02
33	Medical, Precision and Optical Instruments,Watches and Clocks	1.00	0.00
16	Tobacco Products	1.00	0.01
17	Textiles	0.94	0.11
31	Electrical Machinery and Apparatus N.E.C.	0.91	0.04
35	Other Transport Equipment	0.83	0.02
34	Motor Vehicles, Trailers and Semi-Trailers	0.68	0.04
29	Machinery and Equipment N.E.C.	0.43	0.04
19	Tanning and Dressing of Leather; Luggage, Handbags and Footwear	0.41	0.01
24	Chemicals and Chemical Products	0.34	0.15
36	Furniture; Manufacturing N.E.C.	0.32	0.01
22	Publishing, Printing and Reproduction of Recorded Media	0.11	0.00
18	Wearing Apparel; Dressing and Dyeing of Fur	0.02	0.01
15	Food Products and Beverages	0.01	0.21
20	Wood and of Products of Wood and Cork, Except Furniture	0.00	0.01
23	Coke, Refined Petroleum Products and Nuclear Fuel	0.00	0.03
26	Other Non-Metallic Mineral Products	0.00	0.06
28	Fabricated Metal Products, Except Machinery and Equipments	0.00	0.03
27	Basic Metals	0.00	0.13
25	Rubber and Plastic Products	0.00	0.05
21	Paper and Paper Product	0.00	0.02

Notes: Figures are computed from ASI data. Sample refers to the years 2000-2001 to 2009-2010 and is restricted to rural areas. All estimates are obtained using sampling weights.

Table 5: Rainfall and Agricultural Productivity

	Log(Crop Yield)	
	(1)	(2)
Log(Rainfall)	0.178***	0.192***
	(0.020)	(0.019)
Log(Rainfall) x Share Irrigated Land		-0.150***
		(0.017)
Observations	6,763	6,469
District FE	Yes	Yes
Year FE	Yes	Yes

Notes: Unit of observation is a district-year. Rainfall refers to total rainfall in June-September. Log crop yield is a weighted average of yields for crops consistently cultivated in the district during all the years in which the data are available, with area cultivated under a given crop used as weight. The variable Share Irrigated Land has been transformed to have mean zero and standard deviation one. Standard errors are clustered at the district level. *** p<0.01 ** p<0.05 * p<0.1

Table 6: Wage Elasticity

	Log(Wage)		
	All	Agricultural	Non-Agricultural
	(1)	(2)	(3)
Log(Rainfall)	0.080***	0.050***	0.111***
	(0.020)	(0.019)	(0.030)
Observations	89,429	44,955	44,474
District FE	Yes	Yes	Yes
Phase-Time FE	Yes	Yes	Yes

Notes: Unit of observation is an individual. Sample is restricted to individuals aged 18 to 60. The regression includes controls for age, gender, landholdings and crop season. Rainfall refers to total rainfall in June-September. Standard errors are clustered at the district level. All estimates are obtained using sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 7: Consumption Elasticity

	Log(Per Capita Consumption Expenditure)			
	All Goods	Food	Non-Food	Manufactured Goods
	(1)	(2)	(3)	(3)
Log(Rainfall)	0.069***	0.015	0.125***	0.079***
	(0.021)	(0.023)	(0.029)	(0.022)
Observations	83,212	83,176	83,206	83,205
District FE	Yes	Yes	Yes	Yes
Phase-Time FE	Yes	Yes	Yes	Yes

Notes: Unit of observation is a household. The regression includes controls for landholdings and crop season. Rainfall refers to total rainfall in June-September. Standard errors are clustered at the district level. All estimates are obtained using sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 8: Firm Production and Employment Elasticities

	Log(Value of Output)	Log(Man-days)	Log(Workers)	Log(Wage)
	(1)	(2)	(3)	(4)
Log(Rainfall)	0.122**	0.066***	0.058***	0.056***
	(0.049)	(0.025)	(0.022)	(0.017)
Observations	17,296	17,270	17,284	17,270
District FE	Yes	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes	Yes
Phase-Industry FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Notes: Unit of observation is a district-industry-year. Industry is defined at the NIC 4-digit level. District-industry-year measures are obtained using sampling weights and are weighted in the regression by the corresponding weight. Rainfall refers to total rainfall in June-September. Value of output is in nominal terms. Number of workers and man-days include all types of firm employees. Wage refers to average real daily wage across firms -- CPI for Agricultural Labourers is used. Daily wage at the firm level is obtained as total compensation during the year divided by total number of man-days. Standard errors are clustered at the district level. *** p<0.01 ** p<0.05 * p<0.1

Table 9: Firm Elasticities by Industry Type

	Log(Value of Output)		Log(Man-days)		Log(Workers)		Log(Wage)	
	Non-tradable	Tradable	Non-tradable	Tradable	Non-tradable	Tradable	Non-tradable	Tradable
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Rainfall)	0.164***	-0.060	0.118***	-0.079	0.110***	-0.090	0.063***	0.036*
	(0.059)	(0.065)	(0.033)	(0.064)	(0.028)	(0.066)	(0.018)	(0.021)
Observations	13,514	3,782	13,497	3,773	13,504	3,780	13,497	3,773
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Unit of observation is a district-industry-year. Industry is defined at the NIC 4-digit level. District-industry-year measures are obtained using sampling weights and are weighted in the regression by the corresponding weight. Rainfall refers to total rainfall in June-September. Value of output is in nominal terms. Number of workers and man-days include all types of firm employees. Wage refers to average real daily wage across firms -- CPI for Agricultural Labourers is used. Daily wage at the firm level is obtained as total compensation during the year divided by total number of man-days. Standard errors are clustered at the district level. *** p<0.01 ** p<0.05 * p<0.1

Table 10: The Effect of NREGA on the Rainfall-Dependence of Agricultural Productivity and Public Employment

	Log(Crop Yield)	Days in Public Employment
	(1)	(2)
Log(Rainfall)	0.178***	-0.008
	(0.020)	(0.013)
Log(Rainfall) x NREGA	0.000	-0.026***
	(0.003)	(0.009)
Observations	6,763	881,601
District FE	Yes	Yes
Phase-Year FE	Yes	Yes

Notes: Unit of observation is a district-year in Column 1 and an individual in Column 2. In Column 2, sample is restricted to individuals aged 18 to 60. The regression in include controls for age, gender, years of schooling, landholdings and crop season. Rainfall refers to total rainfall in June-September. Standard errors are clustered at the district level. All estimates are obtained using sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 11: The Effect of NREGA on Wage Elasticity

	Log(Wage)		
	All	Agricultural	Non-Agricultural
	(1)	(2)	(3)
Log(Rainfall)	0.062***	0.057***	0.075***
	(0.018)	(0.018)	(0.021)
Log(Rainfall) x NREGA	-0.053***	-0.047***	-0.049***
	(0.013)	(0.018)	(0.018)
Observations	193,602	92,106	101,496
District FE	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes

Notes: Unit of observation is an individual. Sample is restricted to individuals aged 18 to 60. The regression includes controls for age, gender, years of schooling, landholdings and crop season. Rainfall refers to total rainfall in June-September. Standard errors are clustered at the district level. All estimates are obtained using sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 12: The Effect of NREGA on Consumption Elasticity

	Log(Per Capita Consumption Expenditure)			
	All Goods	Food	Non-Food	Manufactured Goods
	(1)	(2)	(3)	(4)
log(Rainfall)	0.056***	0.028**	0.083***	0.063***
	(0.013)	(0.012)	(0.017)	(0.014)
log(Rainfall) x NREGA	-0.052***	-0.043***	-0.060***	-0.034***
	(0.011)	(0.010)	(0.015)	(0.012)
Observations	223,323	223,254	223,315	223,313
District FE	Yes	Yes	Yes	Yes
Phase-Time FE	Yes	Yes	Yes	Yes

Notes: Unit of observation is a district-year in Column 1 and an individual in Columns 2-5. In Columns 2-5, sample is restricted to individuals aged 18 to 60. The regressions in 2-5 include controls for age, gender, landholdings and crop season. Rainfall refers to total rainfall in June-September. Standard errors are clustered at the district level. All estimates are obtained using sampling weights. *** p<0.01, ** p<0.05, * p<0.1

Table 13: The Effect of NREGA on Firm Production and Employment Elasticities

	Log(Wage)	Log(Value of Output)			Log(Man-days)			Log(Workers)		
		All	Non-tradable	Tradable	All	Non-tradable	Tradable	All	Non-tradable	Tradable
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(Rainfall)	0.043***	0.096***	0.126***	0.011	0.044**	0.069***	-0.020	0.040**	0.062***	-0.027
	(0.012)	(0.035)	(0.041)	(0.078)	(0.020)	(0.025)	(0.061)	(0.018)	(0.023)	(0.057)
Log(Rainfall) x NREGA	-0.032**	-0.038	-0.086*	0.138	-0.016	-0.044	0.042	-0.005	-0.030	0.031
	(0.014)	(0.037)	(0.044)	(0.091)	(0.027)	(0.028)	(0.060)	(0.026)	(0.027)	(0.057)
Observations	31,911	31,984	25,097	6,887	31,911	25,046	6,865	31,940	25,063	6,877
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Unit of observation is a district-industry-year. Industry is defined at the NIC 4-digit level. District-industry- year measures are obtained using sampling weights and are weighted in the regression by the corresponding weight. Rainfall refers to total rainfall in June-September. Value of output is in nominal terms. Number of workers and man-days include all types of firm employees. Wage refers to average real daily wage across firms -- CPI for Agricultural Labourers is used. Daily wage at the firm level is obtained as total compensation during the year divided by total number of man-days. Standard errors are clustered at the district level. *** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table 14: The Effect of NREGA on Firm Production and Employment Elasticities by NREGA Phase

	Log(Value of Output)			Log(Man-days)			Log(Workers)		
	All	Non-tradable	Tradable	All	Non-tradable	Tradable	All	Non-tradable	Tradable
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Log(Rainfall) x Phase 1-2	0.321***	0.355***	-0.046	0.153***	0.195***	-0.032	0.139***	0.185***	-0.047
	(0.073)	(0.074)	(0.174)	(0.050)	(0.050)	(0.116)	(0.042)	(0.039)	(0.110)
Log(Rainfall) x Phase 1-2 x NREGA	-0.104*	-0.160**	0.121	-0.079*	-0.119**	-0.030	-0.063*	-0.105**	-0.018
	(0.054)	(0.075)	(0.143)	(0.041)	(0.046)	(0.095)	(0.037)	(0.041)	(0.089)
Log(Rainfall) x Phase 3	0.031	0.055	0.024	0.014	0.032	-0.017	0.012	0.026	-0.022
	(0.039)	(0.044)	(0.082)	(0.021)	(0.026)	(0.064)	(0.020)	(0.025)	(0.059)
Log(Rainfall) x Phase 3 x NREGA	-0.020	-0.063	0.163	0.015	-0.007	0.101	0.022	0.005	0.074
	(0.042)	(0.051)	(0.119)	(0.032)	(0.032)	(0.084)	(0.031)	(0.030)	(0.081)
Observations	31,984	25,097	6,887	31,911	25,046	6,865	31,940	25,063	6,877
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Unit of observation is a district-industry-year. Industry is defined at the NIC 4-digit level. District-industry-year measures are obtained using sampling weights and are weighted in the regression by the corresponding weight. Rainfall refers to total rainfall in June-September. Value of output is in nominal terms. Number of workers and man-days include all types of firm employees. Wage refers to average real daily wage across firms -- CPI for Agricultural Labourers is used. Daily wage at the firm level is obtained as total compensation during the year divided by total number of man-days. Standard errors are clustered at the district level. *** $p<0.01$ ** $p<0.05$ * $p<0.1$

Table 15: Robustness Checks: Alternative Rainfall Measures

	Log(Value of Output)		Log(Man-days)		Log(Workers)		Log(Wage)	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Rainfall Shock	0.060*		0.030*		0.025*		0.037***	
	(0.032)		(0.016)		(0.014)		(0.008)	
Rainfall Deviation		0.143**		0.081***		0.072***		0.060***
		(0.058)		(0.027)		(0.024)		(0.018)
Observations	17,296	17,296	17,270	17,270	17,284	17,284	17,270	17,270
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Unit of observation is a district-industry-year. Industry is defined at the NIC 4-digit level. District-industry-year measures are obtained using sampling weights and are weighted in the regression by the corresponding weight. The variable Rainfall Shock equals one if monsoon rainfall is greater than the district's eightieth percentile of monsoon rainfall, zero if between the twentieth and eightieth percentiles, and minus one if below the twentieth percentile. The variable Rainfall Deviation is the fractional deviation from the the district's mean monsoon rainfall. Value of output is in nominal terms. Number of workers and man-days include all types of firm employees. Wage refers to average real daily wage across firms -- CPI for Agricultural Labourers is used. Daily wage at the firm level is obtained as total compensation during the year divided by total number of man-days. The specification includes the standardized district share of irrigated land and district share of population in agriculture interacted with the rainfall variable. Analysis is restricted to a balanced panel of districts with at least 20 percent of population in agriculture. Standard errors are clustered at the district level. *** p<0.01 ** p<0.05 * p<0.1

Table 16: Robustness Checks: Alternative Classifications of Tradable vs. Non-Tradable Industries

	Panel A: Geographical Concentration Based Classification							
	Log(Value of Output)		Log(Man-days)		Log(Workers)		Log(Wage)	
	Non-tradable	Tradable	Non-tradable	Tradable	Non-tradable	Tradable	Non-tradable	Tradable
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Rainfall)	0.128**	-0.022	0.067**	0.007	0.065***	-0.002	0.059***	0.044
	(0.050)	(0.121)	(0.028)	(0.083)	(0.025)	(0.072)	(0.016)	(0.031)
Observations	14,071	3,063	14,052	3,057	14,060	3,063	14,052	3,057
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
	Panel B: International Trade Based Classification							
	Log(Value of Output)		Log(Man-days)		Log(Workers)		Log(Wage)	
	Non-tradable	Tradable	Non-tradable	Tradable	Non-tradable	Tradable	Non-tradable	Tradable
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Log(Rainfall)	0.137**	0.054	0.075***	0.047	0.070***	0.030	0.068***	0.048**
	(0.065)	(0.059)	(0.028)	(0.051)	(0.026)	(0.046)	(0.017)	(0.023)
Observations	10,829	6,129	10,811	6,121	10,822	6,124	10,811	6,121
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Industry FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Unit of observation is a district-industry-year. Industry is defined at the NIC 4-digit level. District-industry-year measures are obtained using sampling weights and are weighted in the regression by the corresponding weight. Rainfall refers to total rainfall in June-September. Value of output is in nominal terms. Number of workers and man-days include all types of firm employees. Wage refers to average real daily wage across firms -- CPI for Agricultural Labourers is used. Daily wage at the firm level is obtained as total compensation during the year divided by total number of man-days. The specification includes the standardized district share of irrigated land and district share of population in agriculture interacted with log-transformed rainfall. Analysis is restricted to a balanced panel of districts with at least 20 percent of population in agriculture. Standard errors are clustered at the district level.
*** p<0.01 ** p<0.05 * p<0.1

Table 17: Placebo Test: Elasticities in Poorly and Highly Irrigated Districts

	Log(Crop Yield)		Log(Value of Output)		Log(Man-days)		Log(Workers)		Log(Wage)	
	Poorly Irrigated	Highly Irrigated	Poorly Irrigated	Highly Irrigated	Poorly Irrigated	Highly Irrigated	Poorly Irrigated	Highly Irrigated	Poorly Irrigated	Highly Irrigated
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Log(Rainfall)	0.352***	0.027*	0.264***	0.032	0.151***	0.036	0.119***	0.042	0.052***	0.038
	(0.048)	(0.015)	(0.053)	(0.075)	(0.032)	(0.045)	(0.030)	(0.044)	(0.017)	(0.040)
Observations	1,972	2,265	5,481	5,034	5,471	5,028	5,474	5,029	5,471	5,028
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Phase-Industry FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Industry-Year FE	No	No	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Notes: Unit of observation is a district-year in Column 1 and district-industry-year in Columns 2-10. A district is defined as poorly (highly) irrigated if less than 20% (more than 60%) of cultivated land is irrigated. Industry is defined at the NIC 4-digit level. District-industry-year measures are obtained using sampling weights and are weighted in the regression by the corresponding weight. Rainfall refers to total rainfall in June-September. Log crop yield is a weighted average of yields for crops consistently cultivated in the district during all the years in which the data are available, with area cultivated under a given crop used as weight. Value of output is in nominal terms. Number of workers and man-days include all types of firm employees. Wage refers to average real daily wage across firms -- CPI for Agricultural Labourers is used. Daily wage at the firm level is obtained as total compensation during the year divided by total number of man-days. Standard errors are clustered at the district level. *** p<0.01 ** p<0.05 * p<0.1

Table 18: Placebo Test: Elasticities with Respect to Non-Monsoon Rainfall

	Log(Crop Yield)	Log(Value of Output)	Log(Man-days)	Log(Workers)	Log(Wage)
	(1)	(2)	(3)	(4)	(5)
Log(Non-Monsoon Rainfall)	0.015**	-0.026	-0.033	-0.027	-0.016
	(0.007)	(0.023)	(0.023)	(0.020)	(0.010)
Observations	6,763	17,296	17,270	17,284	17,270
District FE	Yes	Yes	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes	Yes	Yes
Phase-Industry FE	No	Yes	Yes	Yes	Yes
Industry-Year FE	No	Yes	Yes	Yes	Yes

Notes: Unit of observation is a district-year in Column 1 and a district-industry-year in Columns 2-5. Industry is defined at the NIC 4-digit level. District-industry-year measures are obtained using sampling weights and are weighted in the regression by the corresponding weight. Rainfall refers to total rainfall in months other than June-September. Value of output is in nominal terms. Number of workers and man-days include all types of firm employees. Wage refers to average real daily wage across firms -- CPI for Agricultural Labourers is used. Daily wage at the firm level is obtained as total compensation during the year divided by total number of man-days.Standard errors are clustered at the district level. *** p<0.01 ** p<0.05 * p<0.1

Table 19: Robustness Check: Firm Elasticities by Input-Output Linkage

	Linked	Non-linked	Non-linked Non-Tradable	Non-linked Tradable
	(1)	(2)	(3)	(4)
	Log(Value of Output)			
Log(Rainfall)	0.140	0.119**	0.150**	-0.059
	(0.110)	(0.054)	(0.065)	(0.063)
	Log(Man-days)			
Log(Rainfall)	0.148*	0.055*	0.106***	-0.087
	(0.078)	(0.028)	(0.034)	(0.061)
	Log(Workers)			
Log(Rainfall)	0.171**	0.038	0.087***	-0.098
	(0.071)	(0.026)	(0.029)	(0.063)
Observations	2,980	14,304	10,632	3,672
District FE	Yes	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes	Yes
Phase-Industry FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Notes: Unit of observation is a district-industry-year. Industry is defined at the NIC 4-digit level. District-industry-year measures are obtained using sampling weights and are weighted in the regression by the corresponding weight. Rainfall refers to total rainfall in June-September. Value of output is in nominal terms. Number of workers and man-days include all types of firm employees. Wage refers to average real daily wage across firms -- CPI for Agricultural Labourers is used. Daily wage at the firm level is obtained as total compensation during the year divided by total number of man-days. Standard errors are clustered at the district level. *** p<0.01 ** p<0.05 * p<0.1

Table 20: Robustness Check: Accounting for Spatial Correlation

	Log(Value of Output)	Log(Man-days)	Log(Workers)	Log(Wage)
	(1)	(2)	(3)	(4)
Log(Rainfall)	0.122**	0.066**	0.058*	0.056***
	(0.049)	(0.033)	(0.031)	(0.015)
Observations	17,296	17,270	17,284	17,270
District FE	Yes	Yes	Yes	Yes
Phase-Year FE	Yes	Yes	Yes	Yes
Phase-Industry FE	Yes	Yes	Yes	Yes
Industry-Year FE	Yes	Yes	Yes	Yes

Notes: Unit of observation is a district-industry-year. Industry is defined at the NIC 4-digit level. District-industry-year measures are obtained using sampling weights and are weighted in the regression by the corresponding weight. Rainfall refers to total rainfall in June-September. Value of output is in nominal terms. Number of workers and man-days include all types of firm employees. Wage refers to average real daily wage across firms -- CPI for Agricultural Labourers is used. Daily wage at the firm level is obtained as total compensation during the year divided by total number of man-days. The specification includes the standardized district share of irrigated land and district share of population in agriculture interacted with log-transformed rainfall. Analysis is restricted to a balanced panel of districts with at least 20 percent of population in agriculture. Standard errors are clustered at the region-year level. *** p<0.01 ** p<0.05 * p<0.1