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Agricultural productivity shocks and poverty in India: The short- and long-term effects of monsoon rainfall

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Non-technical summary

Research Question

Inflation in India strongly depends on fluctuations in food prices, given that food accounts for roughly half of the representative consumption basket. The most important source of uncertainty for the Indian agricultural sector — and therefore also for food prices — are variations in monsoon rainfall. In particular, droughts reduce agricultural yield, dampen wages of agricultural labourers and increase food prices. If droughts are limited to certain districts, migration and arbitrage trading may act as stabilisation mechanisms. However, if larger areas are affected, incomplete trade networks may lead to large movements in wages and food prices. The combination of falling wages and rising food prices is particularly harmful to the rural poor. The current paper therefore attempts to quantify the effects of monsoon rainfall shocks on yield, wages, and food prices in the Indian agricultural sector.

Contribution

To quantify the *dynamic* effects of rainfall variations, we estimate a non-linear panel VAR based on data from 310 Indian districts over the period 1967-2005. In contrast to a static framework, we thus capture the long-lasting effects that arise from sluggish price and wage responses in agricultural markets. Moreover, we distinguish between positive and negative monsoon rainfall shocks to account for their asymmetric effects and explicitly consider the spatial dimension (local/regional) of monsoon rainfall shocks.

Results

Regional droughts lead to an enormous decline in agricultural yield, which is about twice as large as after a local drought. In either case, the size of the short-lived drop in local agricultural yield depends on the local extent of irrigation. After a regional drought, the drop in local agricultural yield elicits a persistent decline (increase) in agricultural wages (food prices). The local extent of irrigation dampens the fall in agricultural wages, but not the rise in food prices. Local droughts only affect agricultural wages (depending on the extent of local irrigation), whereas food prices remain unaffected. The effects of excessive rainfall, on the other hand, are rather limited. Moreover, we find that regional droughts have important distributional consequences. Owing to the persistent decline in wages and the persistent rise in food prices, real income of agricultural labourers deteriorates particularly in the medium run.

Nichttechnische Zusammenfassung

Fragestellung

Die Preissteigerungsrate in Indien wird entscheidend von der Entwicklung der Preise für Lebensmittel beeinflusst, die in ihrer Summe etwa die Hälfte des repräsentativen Warenkorbs ausmachen. Schwankungen der Niederschlagsmenge während der Monsunzeit sind der wichtigste Unsicherheitsfaktor für die indische Landwirtschaft und somit auch für die Preisbildung bei Lebensmitteln. Dürren führen zu verringertem landwirtschaftlichen Ertrag, geringeren Löhnen und höheren Lebensmittelpreisen. Falls Dürren lokal begrenzt bleiben, können die Auswirkungen durch Stabilisierungsmechanismen wie z.B. Arbeitsmigration und Handel gemildert werden. Sind hingegen ganze Regionen von einer Dürre betroffen, sind aufgrund von Handelshemmnissen große Lohn- und Preisschwankungen möglich. Die Kombination von fallenden Löhnen und steigenden Lebensmittelpreisen wirkt sich insbesondere auf die ärmsten ländlichen Bevölkerungsschichten nachteilig aus. Daher untersuchen wir die quantitativen Auswirkungen von Schwankungen der Niederschlagsmenge während der Monsunzeit auf Erträge, Löhne und Preise im indischen Agrarsektor.

Beitrag

Um die dynamischen Effekte von Schwankungen der Niederschlagsmenge zu beziffern, wird ein nicht-lineares Panel-Vektorautoregressionsmodell entwickelt und mit Hilfe von Daten aus 310 indischen Distrikten für den Zeitraum der Jahre 1967-2005 geschätzt. Im Gegensatz zu einem herkömmlichen statischen Ansatz kann ein solches Modell die – durch Lohn- und Preisrigiditäten verursachten – langanhaltenden Auswirkungen auf Löhne und Preise abbilden. Zudem wird sowohl zwischen positiven und negativen Abweichungen der Niederschlagsmenge vom Normalwert unterschieden als auch die räumliche (lokal/regional) Ausdehnung der Schwankungen der Niederschlagsmenge explizit berücksichtigt.

Ergebnisse

Regionale Dürren führen zu einem starken Rückgang des landwirtschaftlichen Ertrags, welcher ungefähr doppelt so stark ausfällt wie nach einer lokal begrenzten Dürre. Der Rückgang des landwirtschaftlichen Ertrags hängt dabei auch von der lokalen Bewässerungsintensität ab. Zudem führt eine regionale Dürre zu einem langanhaltenden Rückgang (Anstieg) der Löhne (Preise) im Agrarsektor. Die lokale Bewässerungsintensität dämpft den Rückgang der Löhne, nicht aber den Anstieg der Lebensmittelpreise. Lokal begrenzte Dürren wirken sich nur auf die Löhne (abhängig von der Bewässerungsintensität), nicht aber auf die Lebensmittelpreise aus. Dagegen bleiben die Auswirkungen von übermäßigem Regenfall eher gering. Darüber hinaus haben insbesondere regionale Dürren spürbare Verteilungswirkungen. Das reale Einkommen der Landarbeiter verringert sich vor allem in der mittleren Frist aufgrund des langanhaltenden Rückgangs der Löhne und des langanhaltenden Anstiegs der Lebensmittelpreise.

Agricultural Productivity Shocks and Poverty in India: The Short- and Long-Term Effects of Monsoon Rainfall*

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Abstract

This paper examines the dynamic effects of monsoon rainfall shocks on yield, wages, and prices in the Indian agricultural sector. We distinguish between positive and negative rainfall shocks and explicitly consider their spatial dimension (local/regional). We find that particularly negative regional shocks exert adverse effects. The enormous drop in agricultural yield is short-lived, but elicits a persistent decline (increase) in wages (food prices). Negative local shocks affect only wages, but not prices. This indicates that, in the food market, intra-regional trading mitigates the impact of local shocks. However, in the labour market, the arbitrage mechanism through migration appears substantially weaker.

Keywords: rainfall shocks, agricultural yield, wages, food prices

JEL classification: C33, E32, O13, Q11.

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1 Introduction

> "Much in India's economy depends on the monsoon. Farming is India's largest employer. Three-fifth of the land under cultivation is watered only by rainfall. Food accounts for almost half of the consumer-price index, so prices ebb and flow with rains. ... A good start to the monsoon makes it more likely that the Reserve Bank of India (RBI) can meet its self-imposed target below 6% ..."
>
> — The Economist, Inflation in India: Of rainfall and price rises, June 25, 2015.

India accounts for about 20% of the world population and (still) about 50% of the Indian workforce is employed in the agricultural sector (Cagliarini and Rush, 2011). Despite huge productivity advances, mainly due to the introduction of high-yield seeds, the increased use of fertilisers, and improvements in irrigation (commonly referred to as the Green Revolution, see IFPRI 2002), a large share of workers in the agricultural sector still lives in precarious conditions and hence is particularly vulnerable to income and price uncertainty (see e.g. Fan, Hazell, and Thorat 1998, Himanshu 2007, Iyengar and Viswanathan 2011). The most important source of uncertainty in the Indian agricultural sector are variations in the amount of monsoon rainfall (Coffey, Papp, and Spears, 2015). The main aim of the current paper is therefore to quantify the transmission channel between monsoon rainfall shocks and the livelihoods of the (poor) rural population in India.

To identify the effects of exogenous rainfall variations, we first standardise monsoon rainfall at the district-level (similarly as in Cole, Healy, and Werker 2012). We thus take into account that farmers may adjust their crop portfolio to differences in mean and variance of monsoon rainfall across districts in India (Pandey and Bhandari, 2007). Second, for each district, we standardise monsoon rainfall also for a region that comprises the district area itself and a surrounding 200km buffer zone. Third, we regress district-wise standardised rainfall on region-wise standardised rainfall. In this way, we obtain two orthogonal rainfall shock series: regional rainfall shocks (i.e. region-wise standardised rainfall) as well as purely local rainfall shocks (i.e. the residuals of the regression). The decomposition of rainfall shocks along the spatial dimension allows us to study the effects of arbitrage trading and migration on food prices and wages. In addition, we find that regional rainfall shocks are not randomly distributed over the monsoon season, but tend to arrive in the months most crucial for crop yield (see also Bhandari, Pandey, Sharan, Naik, Hirway, Taunk, and Sastri, 2007). Fourth, following Lahiri and Roy (1985) and Gadgil and Gadgil (2006), we distinguish between negative (droughts) and positive (excessive) rainfall shocks. To quantify the effects of rainfall variations on agricultural yield, wages and food prices, we then estimate a non-linear panel VAR based on data from 310 Indian districts over the period 1967-2005. In contrast to a static framework, this dynamic approach is able to capture the long-lasting effects that arise from sluggish price and wage responses in agricultural markets. We also control for the effects of variations in annual temperature and the extent of irrigation across districts and over time.

Our main result is that regional droughts lead to an enormous decline in local agricultural yield, which is about twice as large as after a local drought. This can be attributed to the fact that regional droughts tend to arrive in the months most crucial for crop yield (see also Bhandari et al., 2007). In either case, the size of the short-lived drop in local agricultural yield depends on the local extent of irrigation. After a regional drought, the drop in local agricultural yield elicits a persistent decline (increase) in agricultural wages (food prices). The local extent of irrigation dampens the fall in agricultural wages, but not the rise in food prices. Local droughts only affect agricultural wages (depending on the extent of local irrigation), whereas food prices remain unaffected. The effects of excessive rainfall, on the other hand, are rather limited — irrespective of the spatial dimension considered.

The evidence suggests that wages are mainly determined by district-level circumstances (rainfall, irrigation), whereas food prices are mainly determined by rainfall at the regional level. This indicates that (*i*) arbitrage trading at the regional level helps to stabilise food prices when droughts are limited to certain districts (*ii*) in the labour market, the arbitrage mechanism through migration is substantially weaker.[1] Moreover, regional droughts have important distributional consequences. In the short-run, agricultural labourers are protected from nominal wage cuts due to downward nominal wage rigidity (see also Kaur, 2014). However, in the medium-run, their income deteriorates in *real* terms — owing to the persistent decline in wages and the persistent rise in food prices. This combination is particularly harmful to the rural poor in face of incomplete credit markets (see Lanjouw and Shariff 2004 and de Janvry and Sadoulet 2009).[2] Our findings thus relate to the hypothesis of Sen (1981), according to which famines — or, more generally, hunger — are not only due to the (direct) shortfall in agricultural yield, but rather to the unaffordability of food. In addition, we find that landowners and especially share croppers/cultivators suffer from the short-term drop in agricultural yield, but may gain from the medium-term rise in prices for agricultural yield that is not used for own consumption.[3] As a result, subsistence farmers that produce less for the market are more severely affected. Furthermore, our results imply that years with excessive rainfall do not compensate for years of drought. Hence, the predicted increase in the variation of monsoon rainfall (see Challinor, Slingo, Turner, and Wheeler 2006 and Christensen, Hewitson, Busuioc, Chen, Gao, Held, Jones, Kolli, Kwon, Laprise, Magaña Rueda, Mearns, Menéndez, Räisänen, Rinke, Sarr, and Whetton 2007) will likely exert adverse effects (see also Guiteras, 2009).

Among the literature that has attempted to quantify the consequences of agricultural productivity shocks on the livelihoods of the poor so far (see e.g. Mooley and Parthasarathy 1982, Adams 1989, Paxson 1992, Rosenzweig and Wolpin 1993, Mueller and Osgood 2009), our paper is most closely related to Jayachandran (2006). The key differences to her approach are that (*i*) we estimate a panel VAR to capture the persistent responses in agricultural yield, wages and food prices (*ii*) we distinguish between positive and negative monsoon rainfall shocks to account

[1]Especially in the first half of our sample, rainfall forecasts used to be unreliable. More recently, better rainfall forecasts have improved the spatial allocation of labour across India (Rosenzweig and Udry, 2014).

[2]Coping strategies to deal with this dilemma include (temporary) migration, long-distance marriages, or increased labour supply. Farmers may also extend the cultivated land area, change crop portfolios, or sell-off livestock (see e.g. Rosenzweig and Stark 1989; Rosenzweig and Wolpin 1993; Dercon 2002; Pandey and Bhandari 2007; or Aragón, Oteiza, and Rud 2018).

[3]See also the literature on the distributional effects of agricultural growth on poverty in India (Ahluwalia, 1978; Saith, 1981; Bell and Rich, 1994; Sen, 1996; Datt and Ravallion, 1998a,b; Bell and Klonner, 2005).

for their asymmetric effects and (*iii*) we consider the spatial dimension of rainfall shocks.

The remainder of this paper is structured as follows: Section 2 presents the data, Section 3 outlines the empirical methodology, and Section 4 discusses the results and their robustness. Finally, Section 5 concludes.

2 Data

This section describes the data used in this paper. Subsection 2.1 outlines the sources and the construction of the final data set, while Subsection 2.2 presents the key descriptive statistics.

2.1 Data Sources

We construct a panel which comprises annual data from 310 Indian districts (defined by 1966 boundaries) between the years 1967-2005. This panel builds largely on the ICRISAT-dataset, which provides comparable data on prices of agricultural products, produced quantities, wages in the agricultural sector, cultivated land area, and the share of irrigated cultivated land across all 310 districts.[4] To measure agricultural yield during the summer monsoon (kharif) season (June-October),[5] we take into account the produced quantities of the following commodities: rice, sugar, sorghum, millet, maize and groundnut as well as the corresponding cultivated land area. More precisely, agricultural yield is defined as the natural logarithm of the amount produced in tons per $1km^2$ for the selected crops, weighted by the cultivated land area:

$$Yield_{n,t} = \left(\sum_i Area_{i,n,t} * \log\left(\frac{Quantity_{i,n,t}}{Area_{i,n,t}}\right)\right) \Big/ \left(\sum_i Area_{i,n,t}\right), \tag{1}$$

where i denotes the crop-type, t the year and n the district. Analogously, we weight the natural logarithm of nominal crop prices (measured at the farm gate) to construct an index of food prices at the district level:[6]

$$Price_{n,t} = \frac{\sum_i Area_{i,n,t} * \log(Price_{i,n,t})}{\sum_i Area_{i,n,t}}. \tag{2}$$

In addition, we use the natural logarithm of male wages in agriculture (in Rupees/day averaged over the agricultural year) and the share of irrigated cultivated land, which is constructed by

[4]We (*i*) exclude all observations before 1967 due to numerous outliers (*ii*) correct misreported prices (by an order of magnitude) before 1970 in 11 districts and (*iii*) set all observations for prices and wages that are reported "0" to "missing". Further, the end of our sample marks the introduction of the "National Rural Employment Guarantee Act" of 2005 (start of implementation: April 2006). Rosenzweig and Udry (2014) find that this act helped to stabilise wages in areas affected by bad weather shocks. In addition, we thus exclude the period of sharp increases in international food prices (2007-08) which led the Indian government to impose export bans and other measures on rice and other essential agricultural commodities.

[5]The length of the kharif season varies by crop and state, but is typically considered to last from June to October. Rainfall in the months July and August accounts for almost 60% of summer monsoon rainfall and for nearly half of annual rainfall in our sample period (but variation across districts is large, see Figure 1).

[6]Depending on the cost structure and mark-ups of food intermediaries, variations in farm prices lead to more or less amplified movements in consumer prices.

dividing the irrigated cultivated land area by the total cultivated land area.[7]

Furthermore, to identify the effects of exogenous rainfall variations, we first standardise summer monsoon rainfall at the district level based on gridded monthly rainfall data from Willmott and Matsuura (2012). More precisely, for each district, we subtract mean summer monsoon rainfall (in centimetres) from actual summer monsoon rainfall and then divide the difference by the corresponding standard deviation (similarly as in Cole et al. 2012):[8]

$$Rain_{n,t} = \frac{Monsoon\ Rainfall_{n,t} - \overline{Monsoon\ Rainfall}_n}{\sqrt{E[(Monsoon\ Rainfall_{n,t} - \overline{Monsoon\ Rainfall}_n)^2]}}. \tag{3}$$

We thus take into account that (*i*) farmers in districts with below-average rainfall tend to plant crops which require less water and vice versa and (*ii*) farmers in districts with high rainfall variation usually plant crop strains and use technologies that reduce the sensitivity of yield to rainfall variations (Pandey and Bhandari, 2007). Second, for each district, we standardise summer monsoon rainfall also for a region that comprises the district area itself and a surrounding 200km buffer zone (see Figure 2, which also shows the underlying rainfall grid).[9] Third, we regress district-wise standardised rainfall on region-wise standardised rainfall:

$$\underbrace{Rain_{n,t}}_{\text{Standardised Rainfall}} = \underbrace{\hat{\beta} Rain_{n200,t}}_{\text{Regional Shock}} + \underbrace{\epsilon_{n,t}}_{\text{Local Shock}}.$$

In this way, we obtain two orthogonal rainfall shock series: regional rainfall shocks (i.e. region-wise standardised rainfall) as well as purely local rainfall shocks (i.e. the residuals of the regression). Accordingly, a one unit change in either the regional or the purely local rainfall shock measure corresponds to a one unit/one standard deviation change in standardised rainfall in the respective district. The resulting contribution of regional (purely local) rainfall shocks to the variance in overall standardised rainfall is 64% (36%). Table 1 provides further summary statistics. More details can be found in Appendix C.

2.2 Data Description

Monsoon rainfall in the kharif season is a crucial determinant of agricultural yield in India (Coffey et al., 2015). To illustrate its variability, Figure 3 depicts a histogram of standardised

[7] Due to limited availability of female wages in agriculture, we restrict our sample to male wages.

[8] This rainfall measure is closely related to the "Standardized Precipitation Index" (McKee, Doesken, Kleist, et al., 1993) developed to classify the severity of droughts (where a value of -1 represents a moderate drought). We also explore the potential role of long-run trends in rainfall across all districts. However, we find little support for any nation-wide pattern.

[9] Note that the average size of an Indian district is about 10,000km^2. A circle with an area of 10,000km^2 has a radius of about 56km. In this stylised case, the circular area corresponds to about 5% of the constructed regional area. Moreover, we note that our results are not sensitive to the exact size of the surrounding buffer zone. In particular, we obtain similar results with 150km or 300km buffer zones. The only noteworthy change is that, with a 300km buffer zone, a negative local rainfall shock leads to a small, but significant increase in food prices. This likely reflects that the buffer area has been extended too far such that local shocks now also include regional variations in rainfall that no longer can be accommodated by food arbitrage trading.

monsoon rainfall at the district level (see Equation 3) as well as the corresponding normal distribution. We observe that the distribution of standardised rainfall matches the normal distribution closely. Extreme positive variations are slightly more likely than extreme negative variations, whereas small negative deviations are more likely than small positive ones.[10] Given the good fit of the normal distribution, positive/negative variations of more than one standard deviation occur in about 16% of years, while the relative frequency of deviations of more than two standard deviations is roughly 2.3%.

Figure 4 illustrates the effects of variations in monsoon rainfall on agricultural yield using a binned scatter plot. To highlight the non-linear relationship, we also present the fitted curve generated by a locally weighted scatter plot smooth (LOWESS) regression.[11] The LOWESS curve indicates that negative deviations in standardised rainfall reduce agricultural yield substantially, while rainfall above the district-mean has only a small negative impact on agricultural yield. This pattern is also well captured by a linear regression with a break point at mean district-wise rainfall.[12] These non-linear effects render consumption smoothing more challenging and imply that rainfall shocks are no longer distributionally neutral in the long run.

Furthermore, Figure 5 shows separate scatter plots at different percentiles of irrigation. We observe that (*i*) agricultural yield increases at higher levels of irrigation and (*ii*) the non-linear relationship is very strong at low levels of irrigation, but becomes weaker at higher levels. This reflects the fact that plant growth no longer depends solely on the supply of water through monsoon rainfall. As expected, the (weak) negative relationship between above-average rainfall and agricultural yield appears to change little at higher levels of irrigation. In our estimation strategy, we therefore control for the interaction effects between rainfall and irrigation.

Moreover, we decompose rainfall shocks along the spatial dimension (see Section 2.1). Regional and purely local rainfall shocks may exert different effects on food prices and wages, which allows us to infer to what extent their adverse effects can be mitigated by arbitrage trading and migration. In addition, we find that regional rainfall shocks are not randomly distributed across the monsoon season, but tend to arrive in the months most crucial for crop yield.[13] In particular, the coefficients of determination in Panel A of Table 2 show that the

[10]For the majority of districts, the Shapiro and Francia (1972) test cannot reject the null hypothesis of normal distribution across years.

[11]In a LOWESS regression, a weighted regression is carried out for each binned observation, where the central observation gets the highest weight and more remote observations receive less weight (Cleveland, 1979).

[12]This pattern is due to the relationship between water-supply and plant growth, which is linear up-to a break point where maximum water demand of a certain plant is met. Beyond this break point, the effect of additional water is zero. This non-linear relationship is well known in the crop science literature and is conceptualised in the “FAO water production function” (see e.g. Steduto, Hsiao, Fereres, and Raes 2012). While the required amount of water differs by crop and climatic region, the LOWESS estimates in Figure 4 suggest that, due endogenous crop selection in the long run, this break point is close to mean standardised rainfall. Guiteras (2009) or Cole et al. (2012), for instance, capture the non-linearity by including a squared term for rainfall.

[13]Bhandari et al. (2007) attribute the higher sensitivity of crop yield to moisture stress in the late kharif season to the facts that (*i*) this period corresponds to the crucial reproductive and grain-filling stage and (*ii*) the late kharif season leaves less opportunities for crop management than the early kharif season (for instance, by replanting or resowing). For this reason, late (early) season droughts reduce agricultural output mainly through a lower crop yield (smaller cultivated land area). The view that the late kharif season is more crucial is shared by Redfern, Azzu, and Binamira (2012), based on experimental evidence presented in Liu, Liao, Oane, Estenor, Yang, Li, and Bennett (2006), Chhinh and Millington (2015), based on evidence from Cambodia,

contribution of regional rainfall shocks to the variance in overall standardised rainfall in June, September, and October is 75%, 77%, and 83%, respectively — whereas, in July and August their contribution is significantly lower (70% and 65%, respectively).[14] Furthermore, Panel B of Table 2 shows that annual agricultural yield responds much more sensitively to overall rainfall variations in the months June, September, and October than to mid-season variations.[15]

Beyond the impact on agricultural yield, the main aim of our paper is to understand the link between monsoon rainfall shocks and the livelihoods of the population in rural India. As argued by Sen (1981), famines — or, more generally, hunger — are not only due to the (direct) shortfall in agricultural yield, but rather to the (un)affordability of food. Thus, the dynamics of income and food prices play a key role here. Figure 6 illustrates the transmission mechanism in a quasi-event study setting. More precisely, we study the impact of negative shocks in standardised rainfall of at least 1.5 standard deviations. In addition, we require that no other negative/positive shock of more than 1 standard deviation has occurred in a window of ± 3 years around the negative shock. We observe that such a shock leads to a sharp decline in rice yield (the main agricultural crop).[16] However, in the year after the shock, rice yield returns quickly back to its pre-shock level. Initially, nominal agricultural wages do not appear to be affected at all. However, in the year after the negative shock, wage growth is stagnant, i.e. wages do not even adjust for inflation. This finding is in line with the degree of downward nominal wage rigidity observed by Kaur (2014). In addition, the graph also suggests that agricultural wages do not return back to their pre-shock trend in the four years following the shock. In other words, the effects are (close to) permanent. On the other hand, in the year of the shock, the rice price increases and remains at levels above its trend for more than two years. In order to capture the long-lasting impact on monsoon rainfall shocks on income and food prices — and therefore on the livelihoods of the population in rural India — we examine its dynamic effects using an estimated panel VAR.

3 Empirical Methodology

The main aim of this paper is to identify the *dynamic* effects of exogenous variations in monsoon rainfall shocks on yield, wages and prices in the Indian agricultural sector, as well as the interdependencies between these variables.[17] For this purpose, we estimate a panel VAR based

Kattelus, Salmivaara, Mellin, Varis, and Kummu (2015), based on evidence from the Ganges-Brahmaputra-Meghna region, and Moonmoon and Islam (2017), also based on experimental evidence. Fischer and Fukai (2003) document how rice plants respond to drought in different seasons/growth stages.

[14]Panel A of Table 2 shows that the estimated coefficients of month-by-month univariate regressions of standardised rainfall on regional rainfall are all (but the June and September value) significantly different from each other. The relative contribution of regional rainfall to overall standardised rainfall variability — given by the coefficient of determination — is a linear transformation of the estimated coefficient.

[15]See Panel C of Table 2 for separate estimates in response to negative and positive rainfall shocks.

[16]Given that only very few negative monsoon rainfall shocks meet these criteria, we use rice yield and prices instead of the composite measures to maximise the available sample size in this exercise.

[17]Related to our work, Jayachandran (2006) studies the *static* effects of changes in agricultural yield on agricultural wages and prices, whereas Jacoby (2016) examines the effects of changes in agricultural prices on rural wages.

on data from 310 Indian districts (Holtz-Eakin, Newey, and Rosen 1988; Abrigo and Love 2016).[18] To control for unobserved heterogeneity at the district level, we apply the Helmert transformation (see Nickell 1981; Arellano and Bover 1995; Balestra and Krishnakumar 2008).[19] Moreover, we demean all variables by state-year fixed effects in order to account for all kinds of variations (e.g. inflation, technological progress, improvements in infrastructure, or trends in other policy variables) at the state level over time.

Importantly, all endogenous variables pass the panel unit-root tests of Breitung (2000) and Im, Pesaran, and Shin (2003), which have been selected following Hall and Mairesse (2005). The outcome of the tests is the same when first cross-sectional averages are subtracted from the series (with the aim of reducing the impact of cross-sectional dependence, see Levin, Lin, and Chu 2002).[20] This means that the dataset meets the two major requirements for the use of a panel VAR: (i) comparability and (ii) stationarity (Neumann, Fishback, and Kantor, 2010). The final step before estimation of the panel VAR is the selection of the optimal lag-length. Based on the outcome of the Andrews and Lu (2001) lag-length selection criterion, we set out to estimate the following third order VAR model:[21]

$$Y_{n,t} = \sum_{i=1}^{3} Y_{n,t-i} A_i + \sum_{i=0}^{3} X_{n,t-i} B_i + u_{s,t} + u_n + e_{n,t} \tag{4}$$

where $Y_{n,t}$ is a vector containing the following four endogenous variables: log agricultural yield, $Yield_{n,t}$, log nominal agricultural wages, $Wage_{n,t}$, log food prices, $Food_{n,t}$, and the change in the irrigation share, $\Delta Irrig_{n,t}$. In the baseline specification, the exogenous rainfall vector, $X_{n,t}$, consists of the following variables: purely local and regional rainfall shocks, $Rain_{r,n,t}$, where the subscript r refers to the spatial dimension of the shock; both additionally interacted with the dummy variable $D_{n,t}$ being equal to one if *overall* monsoon rainfall is below the district mean, $Rain_{n,t} < 0$, and zero otherwise: $Rain_{r,n,t} \times D_{n,t}$. This specification captures the different effects of negative and positive rainfall variations. In addition, all rainfall variables are interacted with the local change in the irrigation share to capture that a higher irrigation share reduces the importance of rainfall variation, i.e. $Rain_{r,n,t} \times \Delta Irrig_{n,t}$ and $Rain_{r,n,t} \times D_{n,t} \times \Delta Irrig_{n,t}$. A_i and B_i denote the estimated coefficient vectors. In addition, $X_{n,t}$ contains the average temperature in each district during the monsoon season as a control variable (taken from the

[18] VAR models capture the interdependencies between multiple variables with less strict identification restrictions than structural models as well as the (potentially persistent) effects of structural shocks (Sims, 1980). An overview on the range of applications of panel VAR models in the macroeconomics and finance literature is provided by Canova and Ciccarelli (2013).

[19] This transformation preserves the orthogonality between transformed variables and lagged regressors, such that the lagged regressors can be used as instruments and the coefficients can be estimated by System GMM (see Arellano and Bond 1991; Arellano and Bover 1995; Blundell and Bond 1998; Judson and Owen 1999; Love and Zicchino 2006).

[20] For the irrigation-share variable, only the unit-root test of Im et al. (2003) suggests stationarity. The unit-root test by Breitung (2000) fails to reject the null. For this reason, the irrigation share is included in first-differences. Results are overall similar when irrigation is included in levels as an endogenous variable, but the pattern of some impulse responses appears less smooth.

[21] The used criterion resembles a panel VAR adoption of the widely used maximum likelihood-based model selection criteria of Akaike (1969).

same source as rainfall data, Willmott and Matsuura, 2012). Finally, u_n and $u_{s,t}$ refers to the district and state-year fixed-effects, respectively, and $e_{n,t}$ denotes the idiosyncratic error term.[22] The stability condition of the panel VAR is satisfied, as all eigenvalues lie inside the unit circle, i.e. all moduli of the companion matrix are strictly less than one (Hamilton 1994; Lütkepohl 2005).

4 Estimation Results

This section presents the estimated impulse response functions. Subsection 4.1 presents our "baseline specification", where we outline the responses of agricultural yield, wages and food prices to four different types of variation in monsoon rainfall: *negative* (i) local and (ii) regional rainfall variation as well as *positive* (iii) local and (iv) regional rainfall variation, all at different levels of irrigation. Subsection 4.2 discusses the implications of the presented findings. Finally, Subsection 4.3 investigates the sensitivity of our results to the following alternative specifications: (I) We no longer control for the irrigation share and/or the spatial dimension of rainfall variation. (II) We no longer distinguish between rainfall variation above and below the district mean, i.e. we implicitly assume that plant growth would be linearly increasing in water supply independent of the overall amount of rainfall. (III) We exclude outlier districts from our sample, i.e. those districts with a rainfall standard deviation below the 5th and above the 95th percentile. (IV) We split the sample into a sample covering the years 1967-1991 and a sample covering the years 1981-2005 to examine the time stability of our results. (V) We investigate if the shocks had different effects in southern and eastern parts of India (were the monsoon arrives early) as compared with the northern and western parts (were the monsoon arrives late).

4.1 Baseline Specification

Negative local rainfall shock: Figure 7 displays the effects of a negative variation in overall standardised rainfall of one standard deviation caused by a purely local rainfall shock when overall standardised rainfall is below its mean. We show the effects at the 25th (12%), 50th (26%) and 75th (47%) percentile of the irrigation share observed in our dataset (the irrigation share at the respective percentile is depicted in brackets). First, we observe that the adverse effects of negative local rainfall shocks on kharif yield are mitigated by irrigation: the size of the negative spike shrinks (in absolute terms) from about -15% at the 25% percentile of irrigation to almost -12% at the median level of irrigation and to slightly above -7% at the 75% percentile of irrigation, but remains always statistically significant. Moreover, Figure 7 also shows that the decline in monsoon rainfall leads to a lagged, but persistent decline in the agricultural wage.[23]

[22] To account for the formation of twelve new Indian states between 1967-2005, we use the most fragmented state-level definition over the entire sample period for the construction of the state-year fixed effects. This accounts for potential anticipation effects to the formation of new states.

[23] Note that the inclusion of state-year fixed effects accounts for general wage and/or price movements within a state over time.

At the first quartile of irrigation, the maximum impact of almost -4% occurs 2 years after the decline in monsoon rainfall. Moreover, the decline in the wage remains significant for up to 5 years after the rainfall shock. The delayed response likely relates to nominal wage rigidities in the Indian agricultural sector as documented by Kaur (2014). Accordingly, downward real wage adjustments occur mainly through inflation and not through cuts in the nominal wage (see also Figure 6). This means that, in the agricultural year following the shock, the immediate effect of a shortfall in monsoon rain leads to a substantial reduction in the income of farmers and sharecroppers, while agricultural labourers suffer only little.[24,25] However, the decline in their income is much more persistent. In contrast, medium and large-scale farmers profit from cheaper labour costs for several years. Moreover, we note that food prices stay essentially unchanged after a local reduction in monsoon rainfall.[26] This likely reflects the accommodating effects of intra-regional arbitrage trading, which avoid any substantial increase in food prices. This is in line with Donaldson (2018), who finds that improvements in infrastructure facilitating trade have substantially reduced the exposure of agricultural prices to rainfall variation in India.[27]

Negative regional rainfall shock: Figure 8 presents the responses of agricultural yield, wages and food prices to a negative variation in overall standardised rainfall of one standard deviation caused by a regional rainfall shock when overall standardised rainfall is below its mean. This corresponds to a general reduction of rainfall in the district itself and the surrounding area with a radius of 200km. In addition, as documented in Section 2.2, regional rainfall shocks are not randomly distributed across the monsoon season, but tend to arrive in the months most crucial for crop yield. Hence, we note that the effects on agricultural yield are now substantially larger, particularly at low levels of irrigation.[28] Again, the effects on agricultural yield are short-lived, having nearly completely disappeared in the following year and being no longer

[24] Cultivators are individuals who farm on their own plot of land and earn the harvest. Share croppers get paid for their work on another person's land in a share of the harvested crops. Agricultural labourers are individuals that get paid in cash for their work. Landowners are individuals that own a large plot of land that requires additional individuals working on it.

[25] In addition, the decline in agricultural wages also tends to reduce sharecroppers' outside options, thereby reducing their share of yield further (see Chaudhuri and Maitra 2000).

[26] We only note a small significant increase in districts with high levels of irrigation. Such districts might contribute disproportionately to regional agricultural output and hence to regional food price formation (see also the following paragraphs). This may explain why the response of food prices at higher levels of irrigation turns significantly positive (albeit the amplitude remains small).

[27] Another institution that potentially mitigates the effects of local rainfall shocks is the Food Corporation of India. This governmental institution aims at stabilizing prices through managing buffer stocks of food grains, distributes food grains through a public distribution system, and regulates market prices for consumers.

[28] In addition, Table 3 examines whether the estimated stronger impact of negative regional rainfall shocks (compared to negative local rainfall shocks) might be caused by an insufficiently high resolution of the gridded rainfall data. In this case, measurement error at the district level would be higher than at the regional level, which potentially could contribute to a higher estimated impact to (more precisely measured) regional rainfall shocks. By contrast, when we split the full sample into "small districts" and "large districts", we observe that the relative impact of regional (vs. purely local) negative rainfall shocks is higher among "large districts" (which are less prone to measurement error). Similarly, the relative impact of regional (vs. purely local) negative rainfall shocks rises when we alternatively use rainfall data from the APHRODITE Dataset, the database with the largest number of weather stations (see Yatagai, Kamiguchi, Arakawa, Hamada, Yasutomi, and Kitoh 2012 for a documentation). The main reason why we do not use the APHRODITE Dataset in the baseline specification is that its station network changes with time and season.

significant.

As compared to local negative rainfall shocks, we observe that the stronger response in agricultural yield translates into a roughly proportionally stronger response in agricultural wages. In particular, the maximum impact on wages is about 50% stronger, even though the effects dissipate somewhat faster about three years after the shock.[29] As in the case of local rainfall shocks, the impact on wages declines with the local level of irrigation and is no longer significant at the 75th percentile. Overall, the evidence suggests that agricultural wages are mainly determined by local circumstances (i.e. the drop in yield which depends on the local level of irrigation) rather than the spatial dimension (local/regional) of the rainfall shock. This indicates that, in the labour market, the arbitrage mechanism through (both, intra- and supra-regional) migration is relatively weak.

Regarding food prices, we now observe an increase of close to 6% in the affected district across all levels of irrigation. We also note that the responses remain significant for up to three years. There is only a very modest impact of irrigation mitigating the initial increase in food prices. The almost uniform increase in food prices thus does not relate directly to the decline of agricultural yield in the district, but rather appears due to a deterioration of the agricultural sector in the whole region. Intra-regional arbitrage trading appears to be quite efficient at reducing the exposure to food price fluctuations due to local circumstances in response to both, local and regional rainfall shocks. However, the significant rise in food prices to negative regional shocks indicates that supra-regional agricultural trade networks in India are still incomplete — even inside states (note that we control for general changes in food prices at the state level). A potential obstacle to supra-regional trade could be the state of India's infrastructure. During our sample period, railways faced severe capacity constraints and freight costs were much higher than in other countries, while road transport was being hindered by small, congested and insufficiently maintained highways. Moreover, even nowadays almost 40% of all Indian villages are still not connected by all-season roads (World Bank, 2018).[30] Interestingly, the observed rise in food prices — a large part of the consumption basket in India — could be the driver of a faster adjustment in the agricultural labour market, as it allows a quicker adjustment of wages in real terms (see also Kaur 2014).

Positive local rainfall shock: Having analyzed the adverse effects of negative rainfall shocks, we now examine the impact of positive variations in monsoon rainfall. Figure 9 presents the responses following a positive variation in overall standardised rainfall of one standard deviation caused by a purely local rainfall shock when overall standardised rainfall is above its mean. We observe that such a shock exerts no significant effects: neither on agricultural yield, nor on wages or food prices at any horizon. This implies that the effects of local rainfall variations

[29]The faster convergence back to normal is likely related to the fact that we control for state-year fixed effects and, in the case of a regional shock, a larger fraction of the state is affected.

[30]For the impact of infrastructure on trade and welfare in Colonial India, see Burgess and Donaldson (2017) and Donaldson (2018).

are strongly asymmetric.[31] Put differently, positive shocks cannot counterbalance the adverse effects caused by negative shocks. This result relates to a crop's production function. Accordingly, maximum yield (with regards to rainfall) is reached when there is enough precipitation to ensure maximum evapotranspiration (Steduto et al., 2012).

Positive regional rainfall shock: Figure 10 presents the responses of agricultural yield, wages and food prices to a positive variation in overall standardised rainfall of one standard deviation caused by a regional rainfall shock when overall standardised rainfall is above its mean. Unlike in the case of positive local shocks, agricultural yield seems to decline initially, then to recover in the following year, but then to decline again before slowly returning back to normal. This pattern is apparent across all levels of irrigation, but the size of the confidence interval increases with the level of irrigation. This means that the response is no longer significant at the 75th percentile of irrigation. There is no significant effect on wages, even though the point estimate seems to suggest a small initial decline, followed by a small increase afterwards. Average (kharif) food prices show no significant response in the year of the shock, but then decline by -3.5% (-2.2%) at the 25th (75th) percentile of irrigation in the following year.

The delayed fall in (kharif) food prices likely reflects an increase in the production of rabi (winter) crops, which profit from additional water supply caused by above-average monsoon rainfall in the kharif season (e.g. through tank irrigation). This might reduce harvest prices of substitutable kharif crops in the following year. Indeed, Figure 11 illustrates that the response of rabi crop yield (prices) to a positive regional rainfall shock in the kharif season is positive (negative).[32] The (renewed) decline in kharif and rabi yield two years after the shock then may be due to reduced farming efforts of agents with adaptive expectations in response to low crop prices in year one after the shock.[33]

4.2 Discussion

Our main result is that (above all, negative regional) monsoon rainfall shocks exert adverse effects on the agricultural sector in India. Moreover, our results imply that the following four social groups are very differently affected: (i) cultivators and share croppers (ii) agricultural labourers, (iii) landowners and (iv) individuals working outside the rural sector. The income of cultivators and share croppers is affected by the change in agricultural yield and the price they

[31] This explains why our estimated elasticities to negative rainfall shocks are two to three times larger than Jayachandran's (2006) symmetric estimate. Other previous studies that have found non-linear effects of rainfall shocks in India include, e.g., Lahiri and Roy (1985) and Gadgil and Gadgil (2006). These papers, however, have a different focus than ours in terms of selected variables and the geographical level of interest.

[32] To generate Figure 11, we additionally include agricultural yield and prices of typical rabi crops (i.e. wheat, barley, mustard, sesame and peas) into the VAR. However, due to limited availability of rabi crop yield and price data (the impulse responses in Figure 11 are estimated with less than half of the observations than those in Figure 10), the presented results should only be seen as an illustration of the potential channel at work (see also e.g. Kulkarni and Kurian 2016). For this reason, the fact that the negative response of kharif yield in Figure 11 is insignificant does not establish a major concern.

[33] An alternative explanation for this phenomenon is the phasing out of flood-support for farmers which stabilised yield in the previous year (which could be due to declining media coverage on the provided flood support over time, see e.g. Besley and Burgess 2002).

receive for their harvest. Thus, the persistent increase in food prices for up to two years after the shock compensates them in part for the one-time loss in agricultural yield. Depending on the irrigation share, the income gain in the years after the shock may even over-compensate them for the initial losses. Agricultural labourers, who typically make up a considerable share of the poorest individuals in rural areas (ILO, 1996), suffer from the delayed decrease in the agricultural wage, which leads to a reduction in their nominal income — after accounting for state-level developments — for a substantial period of time. Furthermore, in real terms, their income falls even stronger, owing to the persistent rise in food prices in the respective district. The income of landowners is initially negatively affected by the drop in agricultural yield. However, in the following periods, they also profit from lower labour costs and higher food prices. The extent of the effects on income depends as seen on both, the irrigation share in the district and whether rainfall variation is local or regional. Finally, individuals working outside the agricultural sector will be affected through the increase in food prices.[34]

Our results thus relate to the work of Sen (1981), according to which famines cannot easily be explained by reductions in agricultural yield alone. Rather, famines are caused by a breakdown of the food acquisition process. The key determinants for the ability of an individual to acquire food are income and food prices. According to Engel's law, when food prices increase, the poorest individuals are over-proportionally affected as they spend a bigger share of their income on (staple) food.[35] Similarly, reductions in wage income of the poor have more severe consequences as they have fewer possibilities to shift expenditure from other consumption to food. Even though India has avoided the occurrence of major famines since its independence in 1947, starvation deaths related to the inability of individuals to acquire food remained a serious problem (Banik, 2006). For example, because starving individuals cannot afford to buy staple food, while at the same time stored grain roots in a neighbouring state (Waldman, 2016).

Moreover, our results suggest that years of above-normal rainfall do not counterbalance the adverse effects in years of below-normal rainfall. Given that rainfall variability is predicted to increase further in the future (see e.g. Dinar, Mendelsohn, Evenson, Parikh, Sanghi, Kumar, McKinsey, and Lonergen 1998, Christensen et al. 2007, Kripalani, Oh, Kulkarni, Sabade, and Chaudhari 2007), this development will likely affect the livelihoods of the poorest in a severe way, particularly of agricultural labourers.[36] We also find that irrigation mitigates the decline in agricultural yield and wages (but hardly the rise in food prices). However, there are strong

[34]In his assessment of the potential benefits of economic reforms in India, Sen (1996) argues that the elasticity of food production with respect to the relative price of food needs to be unrealistically high (greater than two), such that increases in food prices help to reduce poverty through increased food production. Moreover, in the same study, Sen (1996) finds that higher agricultural wages are associated with lower levels of rural poverty.

[35]In contemporary India, Engel's law rather applies to staple foods than to overall food consumption. In particular, Li (2016) finds that, with rising income, households start to consume also more expensive varieties in addition to staple food (but do not substitute away from staple food). This may explain why the income share spent on overall food consumption remains relatively stable at about 73% for the first three income deciles before eventually declining (Ravallion, 2000).

[36]The projections of the climate models used by Kripalani et al. (2007) are based on the scenario that the atmospheric CO_2 concentration doubles. In addition to an increase in the frequency of extreme rainfall shocks, most climate models also project an increase in mean rainfall. Taken in isolation, this might exert beneficial effects for the agricultural sector in India as long as water management adjusts appropriately to the new situation.

doubts about the sustainability of the current extent of irrigation. According to Bansil (2004), current excessive irrigation leads to dwindling levels of groundwater. Thus, the Indian agricultural sectors risks falling back into rainfall dependence (Hertel, 2015), while at the same time rainfall variability is predicted to increase.

4.3 Sensitivity Analysis

In the following, a number of robustness checks are presented.[37] In the first variant, we distinguish neither between the spatial dimension (local vs. regional) of the shock nor by the level of irrigation at the district-level, i.e. we use overall rainfall variation as exogenous source of variation (see Figure 12). As expected, the size of the responses in agricultural yield to an overall negative rainfall shock is in-between the response to a local and a regional shock (each at the median level of irrigation). The same applies to the response of the agricultural wage (with wider confidence bands at short horizons, tighter confidence bands at longer horizons) and the response of food prices. The main conclusion from this exercise is that the signs of the impulse responses are robust, even if the extent of irrigation and the spatial dimension of rainfalls shocks are not accounted for.

Similarly, Figure 13 shows the impulse responses when we control for the spatial dimension of the rainfall shock, but not for the level of irrigation, whereas Figure 14 shows the impulse responses when we control for the level of irrigation, but not for the spatial dimension of the shock. The estimated impulse responses highlight three findings: (*i*) Wages seem to be determined at the local level. Hence, taking rainfall in the surrounding area additionally into account changes the amplitudes of the responses only little. Instead, the amplitudes vary substantially with local characteristics like the level of irrigation. (*ii*) Food prices seem to be determined at the regional level. Thus, the amplitude of their impulse response changes substantially when we distinguish between local and regional shocks. On the other hand, local characteristics (like irrigation) seem to play only a minor role. (*iii*) The responses of agricultural yield depend on both, the local level of irrigation and the spatial dimension of the rainfall shock. However, we find that regional rainfall shocks are not randomly distributed over the monsoon season, but tend to arrive in the months most crucial for crop yield (Bhandari et al., 2007). Hence, it is unlikely the spatial dimension as such which exerts these effects. Overall, these results indicate that arbitrage trading at the regional level helps to stabilise food prices when droughts are limited to certain districts. In the labour market, however, the arbitrage mechanism through migration seems substantially weaker.

Figure 15 depicts the impulse responses of agricultural yield, wages and food prices when we assume that the effect of additional water on crop growth is linear. Qualitatively, the impulse responses resemble those to negative rainfall shocks (when the nonlinear relationship is explicitly considered), but with substantially lower amplitudes (in absolute terms).[38] Thus, the

[37]To facilitate comparison, we choose the same lag-length as in the baseline specification in all robustness checks.

[38]Yet, note that the response of agricultural yield to regional rainfall shocks now seems persistent. In addition, wages appear not responsive to local rainfall shocks.

results seem to suggest that additional rainfall always exerts a positive effect on agricultural yield and wages, while reducing food prices when the shock is regional. We also observe, as in the baseline specification, that irrigation mediates the impact of monsoon rainfall shocks on agricultural yield and wages. However, the conclusion drawn from this result would be different — as also the apparently beneficial effects to positive rainfall shocks would be mediated. By contrast, in the baseline specification, only the adverse effects of negative rainfall shocks are mediated, whereas irrigation has little impact on the effects of positive rainfall shocks.

Next, we exclude outlier districts from the sample, i.e., we use only those districts that lie between the 5th and 95th percentile of rainfall standard deviation (in centimetres). Figure 16 shows that the responses of agricultural yield to a negative and local regional rainfall shock remain nearly identical. Also the estimated response of agricultural wages stays almost the same, but with tighter confidence intervals. This indicates that — despite the smaller sample size — the effects of rainfall shocks are more precisely estimated when districts with very low and very high rainfall variation are excluded. Regarding food prices, the pattern remains also very similar. We only note that, in the case of a negative regional shock, the effect on food prices is about one percentage point smaller than in the full sample (but the general conclusions remain the same). Figure 17 depicts that also the responses to (both, local and regional) positive rainfall shocks are very robust to the exclusion of outlier districts.[39]

To examine the time stability of our results, we estimate the impulse responses for two sub-samples. The early subsample covers the years 1967-1991 (see Figures 18 and 19), while the late sub-sample ranges from 1981-2005 (see Figures 20 and 21).[40] The estimates appear to be broadly in line with our baseline specification. The most interesting change over time seems that the rise in food prices after a negative regional shock appears to be stronger and more persistent in the early sub-sample. This likely reflects improvements in transport infrastructure (beyond those captured by state-year fixed effects),[41] which helped to increase supra-regional trade and, thus, reduced supra-regional price gaps that arise after rainfall shocks.[42] Similarly, the response of wages to negative local rainfall shocks is no longer significant at any level of irrigation in the late sub-sample, which might indicate improved migration conditions. In addition, we find that agricultural yield rises about one to three years after (both, local and regional) positive rainfall shocks in the early sub-sample, but not later on. This potentially reflects that irrigation systems in the early sub-sample were typically based on irrigation tanks and, hence, relied mostly on previous rainfall. By contrast, modern irrigation systems in the late sub-sample used mostly technologies which depend less on previous rainfall, e.g. tube wells.

Finally, we compare the estimated impulse responses for districts in southern and eastern parts of India were the monsoon arrives usually before the 10-15th of June (see Figures 22

[39]Also, our results are robust when we exclude districts above an altitude of 600m, where the relationship between rainfall and crop yield is weaker (as suggested by Jayachandran 2006).

[40]We estimate two overlapping sub-samples to achieve a sufficiently large number of degrees of freedom.

[41]Note that the state-year fixed effect do not necessarily capture interaction effects between (local/regional) rainfall and infrastructure.

[42]See Donaldson (2018) for a study on the impact of railroad network extensions in Colonial India between 1853 and 1930.

and 23) with the estimated impulse responses for districts in northern and western parts of India were the monsoon arrives usually after the 10-15th of June (see Figures 24 and 25). We find that the adverse effects of negative regional rainfall shocks are substantially stronger in the south-east than in the north-west of India. In addition, agricultural yield in the south-east falls significantly (at low and medium levels of irrigation) in response to positive local rainfall shocks, whereas we observe even a small significant increase in agricultural yield (at high levels of irrigation) in the north-west. Also the decline in food prices after a positive regional shock is much more pronounced in the north-west. In summary, we conclude that the agricultural sector in south-east India appears more vulnerable to monsoon rainfalls shocks than in the north-west.

5 Conclusion

This paper examines the dynamic effects of monsoon rainfall shocks on yield, wages, and prices in the Indian agricultural sector. We distinguish between positive and negative rainfall shocks and explicitly consider their spatial dimension (local/regional). In addition, we also control for the effects of variations in annual temperature and the extent of irrigation across districts and over time. Our main result is that regional droughts — which tend to arrive in the months most crucial for crop yield (see also Bhandari et al., 2007) — lead to an enormous decline in local agricultural yield, which is about twice as large as after a local drought. In either case, the size of the short-lived drop in local agricultural yield depends on the local extent of irrigation. After a regional drought, the drop in local agricultural yield elicits a persistent decline (increase) in agricultural wages (food prices). The local extent of irrigation dampens the fall in agricultural wages, but not the rise in food prices. Local droughts only affect agricultural wages (depending on the extent of local irrigation), whereas food prices remain unaffected. The effects of excessive rainfall, on the other hand, are rather limited — irrespective of the spatial dimension considered.

The evidence suggests that agricultural wages are mainly determined by local circumstances (rainfall, irrigation), whereas food prices are mainly determined by rainfall at the regional level. This indicates that (*i*) arbitrage trading at the regional level helps to stabilise food prices when droughts are limited to certain districts (*ii*) in the labour market, the arbitrage mechanism through migration is substantially weaker. Moreover, the observed pattern indicates that particularly regional droughts have important distributional consequences. In the short-run, agricultural labourers are protected from nominal wage cuts due to downward nominal wage rigidity. However, in the medium-run, income of agricultural labourers deteriorates in *real* terms — owing to the persistent decline in wages and the persistent rise in food prices. This combination is particularly harmful to the rural poor in face of incomplete credit markets (see Lanjouw and Shariff 2004 and de Janvry and Sadoulet 2009). Our findings thus relate to the hypothesis of Sen (1981), according to which famines — or, more generally, hunger — are not only due to the (direct) shortfall in agricultural yield, but rather to the unaffordability of food. In addition, we find that landowners and especially share croppers/cultivators suffer from the short-term drop in agricultural yield, but may gain from the medium-term rise in prices for agricultural yield that is not used for own consumption. As a result, subsistence farmers that produce less for the market are more severely affected.

Furthermore, our results imply that years with above-normal rainfall do not compensate for the adverse effects in years of below-normal rainfall. Hence, the predicted increase in the variation of monsoon rainfall (see Challinor et al. 2006 and Christensen et al. 2007) will likely exert adverse effects (see also Guiteras, 2009), also because there are strong doubts about the sustainability of the current extent of irrigation. According to Bansil (2004), current excessive irrigation leads to dwindling levels of groundwater. Thus, the Indian agricultural sector risks falling back into rainfall dependence (Hertel, 2015), while at the same time rainfall variability is predicted to increase.

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Appendix

A Figures

A.1 Climate Diagram Kurnool District

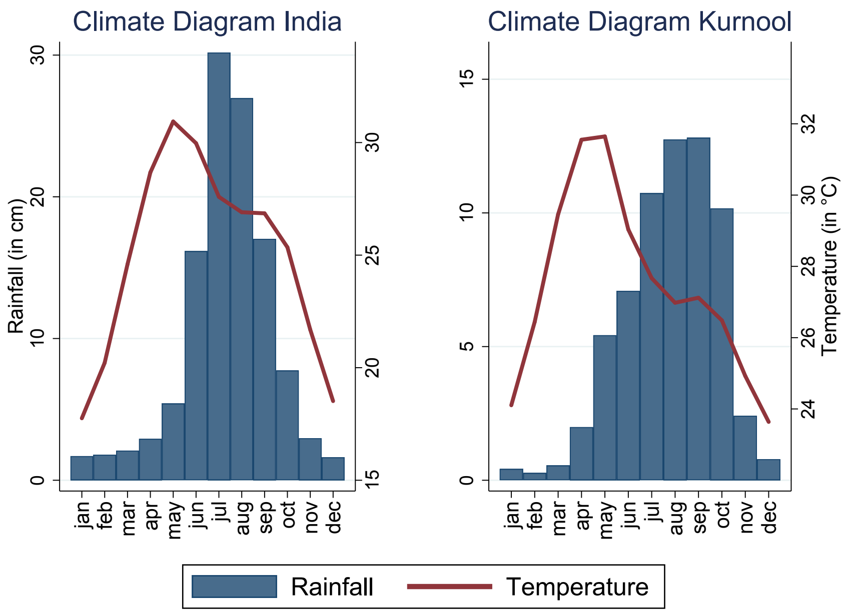


Figure 1: The figure depicts the climate diagram over the period 1967-2005 for entire India (on the left) and the Kurnool district in Andhra Pradesh (on the right). The data source is Willmott and Matsuura (2012).

A.2 Buffer Area Illustration

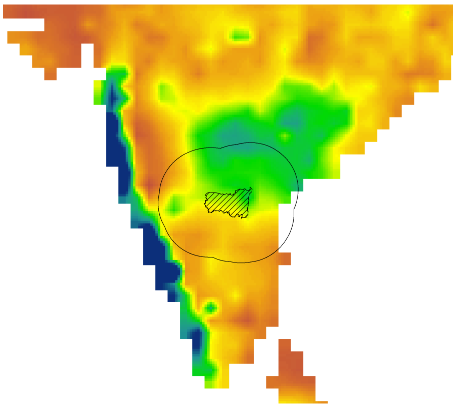


Figure 2: The figure depicts the Kurnool district in the state of Andhra Pradesh with an area of 17,626 km^2 (shaded area). The average size of an Indian district is about 10,000 km^2. The area surrounding the district is the 200km buffer area. The areas are calculated using a projected coordinate system — a two-dimensional approximation of the earth surface — of the Indian subcontinent. The underlying data illustrates the amount of rainfall in August 2000 (red to blue cells reflect higher rainfall in centimetres), which is used for constructing rainfall in districts and buffer areas.

A.3 Rainfall Variation in India

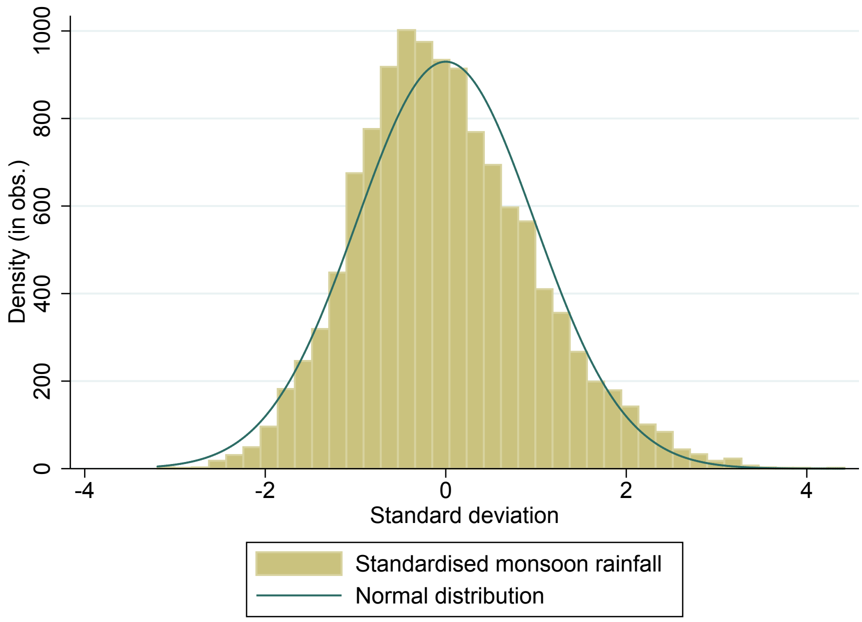


Figure 3: The figure depicts the standard normal distribution and the distribution of standardised monsoon rainfall as defined in Equation 3.

A.4 Rainfall Variation and Agricultural Yield

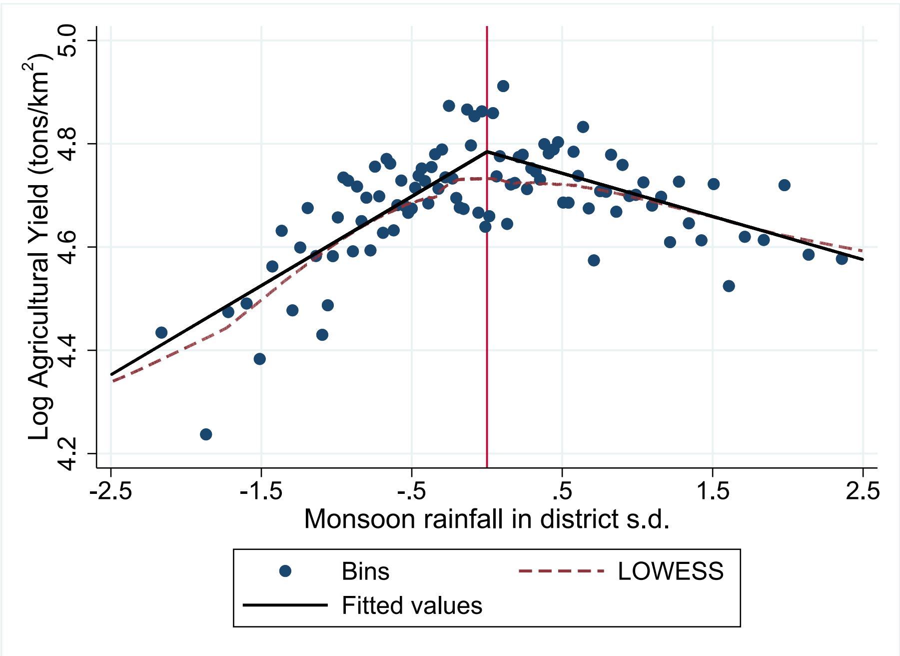


Figure 4: The figure presents a binned scatterplot (100 bins with ≈ 104 observations each) for variations in monsoon rainfall and log agricultural yield. To outline the effect of monsoon rainfall on agricultural yield "Locally Weighted Scatterplot Smoothing" (LOWESS) and linear spline fitted values are added (these values have been created using the full dataset, while for illustration purposes the x-axis has been restricted to the range from -2.5 to 2.5).

A.5 Rainfall Variation, Agricultural Yield and Irrigation

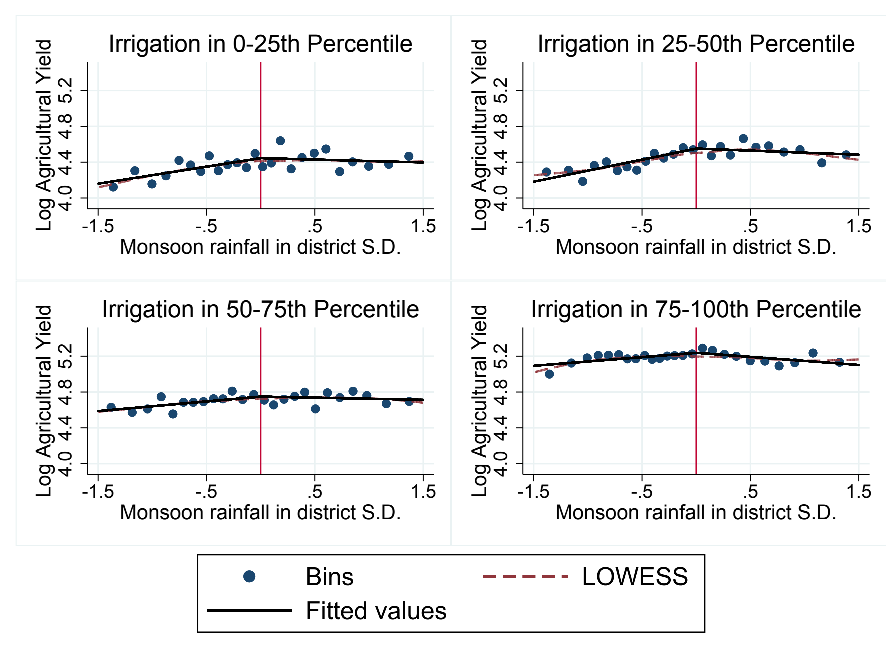


Figure 5: The figure presents binned scatterplots (25 bins per plot) for variations in monsoon rainfall and log agricultural yield at different percentiles of irrigation. We also show Locally Weighted Scatterplot Smoothing (LOWESS) and linear spline fitted values.

A.6 Effect of Monsoon Shock on Yield, Wages, and Prices

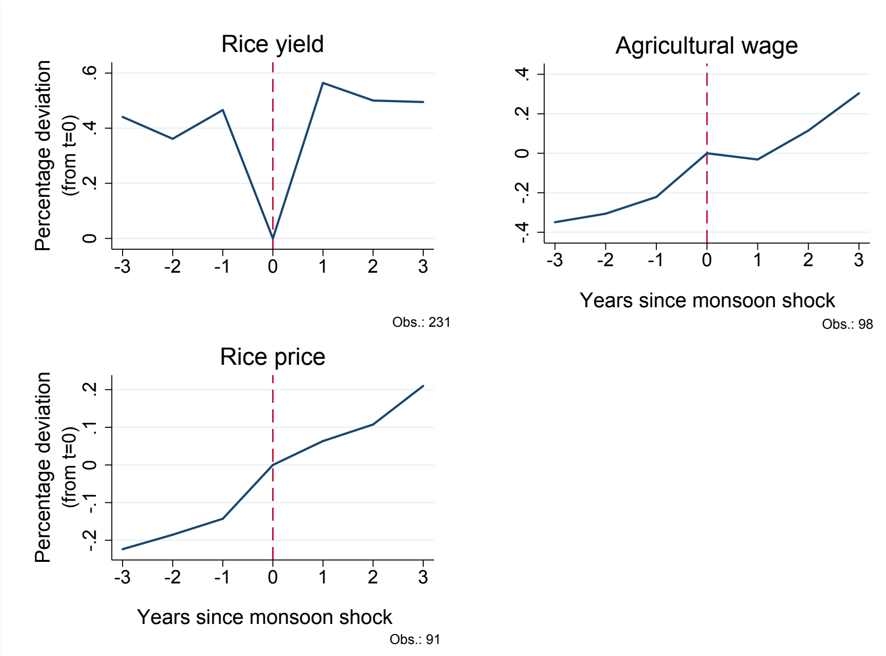


Figure 6: The graphs illustrate an event study for observed negative rainfall shocks of below -1.5 district standard deviation (SD), occurring at t=0, while in the remaining time period no single shock above/below 1 standard deviation has occurred. Only balanced data is used for plotting the graphs.

A.7 Response to Negative Local Rainfall Variation

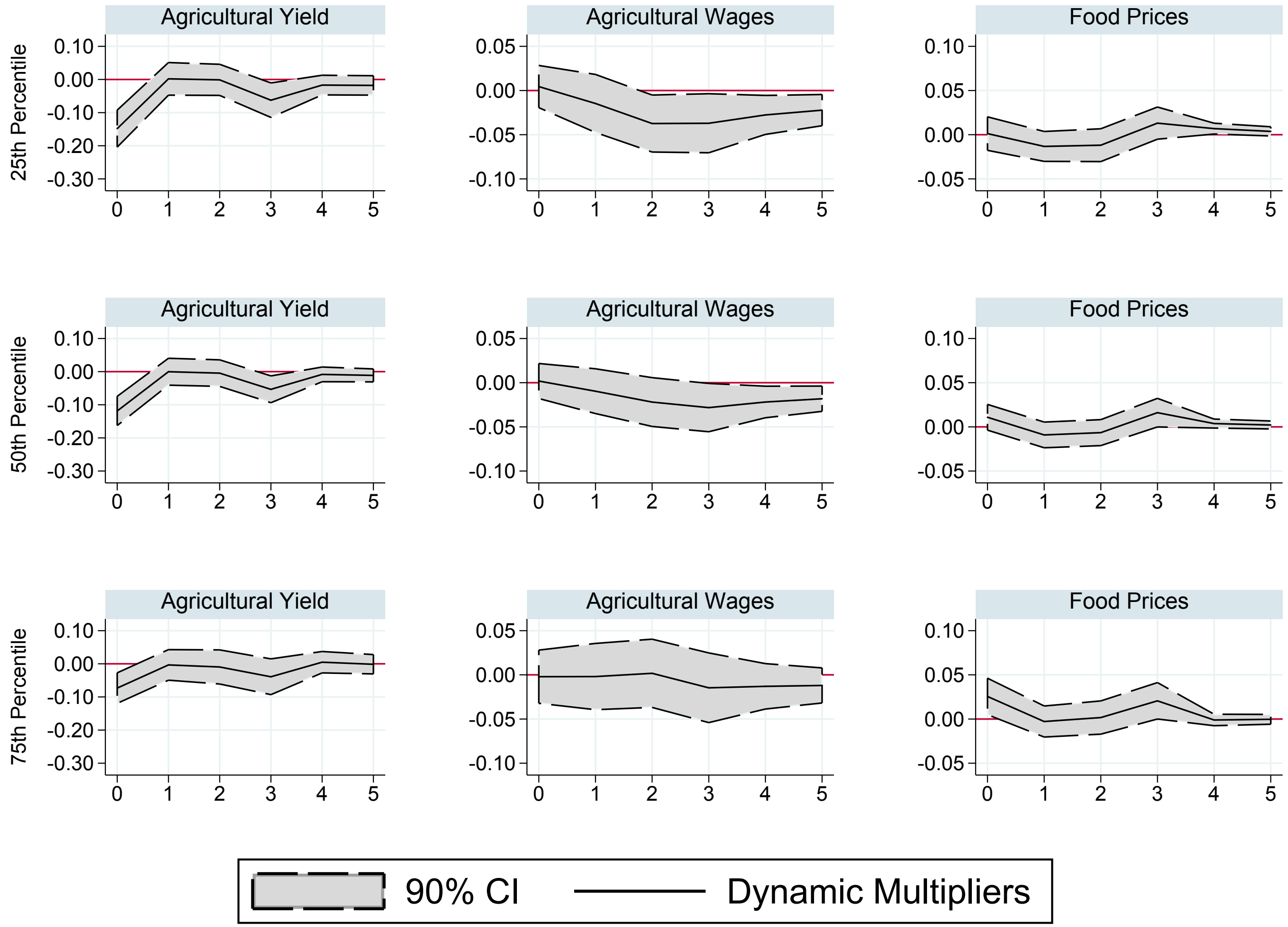


Figure 7: The figure illustrates the impulse responses to a negative variation in overall standardised kharif rainfall of one standard deviation caused by a purely local rainfall shock when overall standardised kharif rainfall is below its mean. The black solid line is the point estimate. The gray area represents the 90% confidence interval over a 5 year time period. The effects are presented for different levels of irrigation. The results are based on 2951 observations at the selected lag-length.

A.8 Response to Negative Regional Rainfall Variation

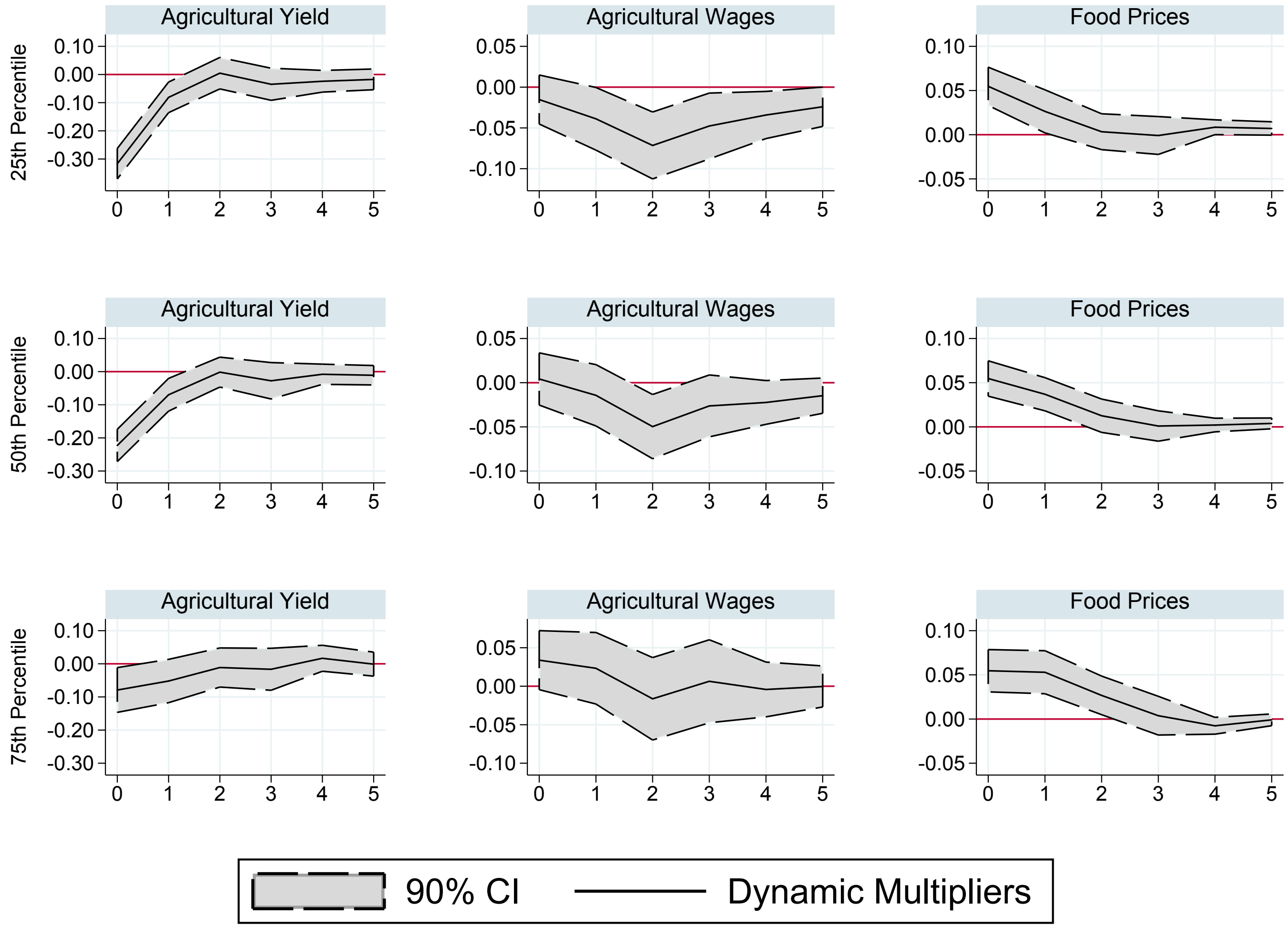


Figure 8: The figure illustrates the impulse responses to a negative variation in overall standardised kharif rainfall of one standard deviation caused by a regional rainfall shock when overall standardised kharif rainfall is below its mean. The black solid line is the point estimate. The gray area represents the 90% confidence interval over a 5 year time period. The effects are presented for different levels of irrigation. The results are based on 2951 observations at the selected lag-length.

A.9 Response to Positive Local Rainfall Variation

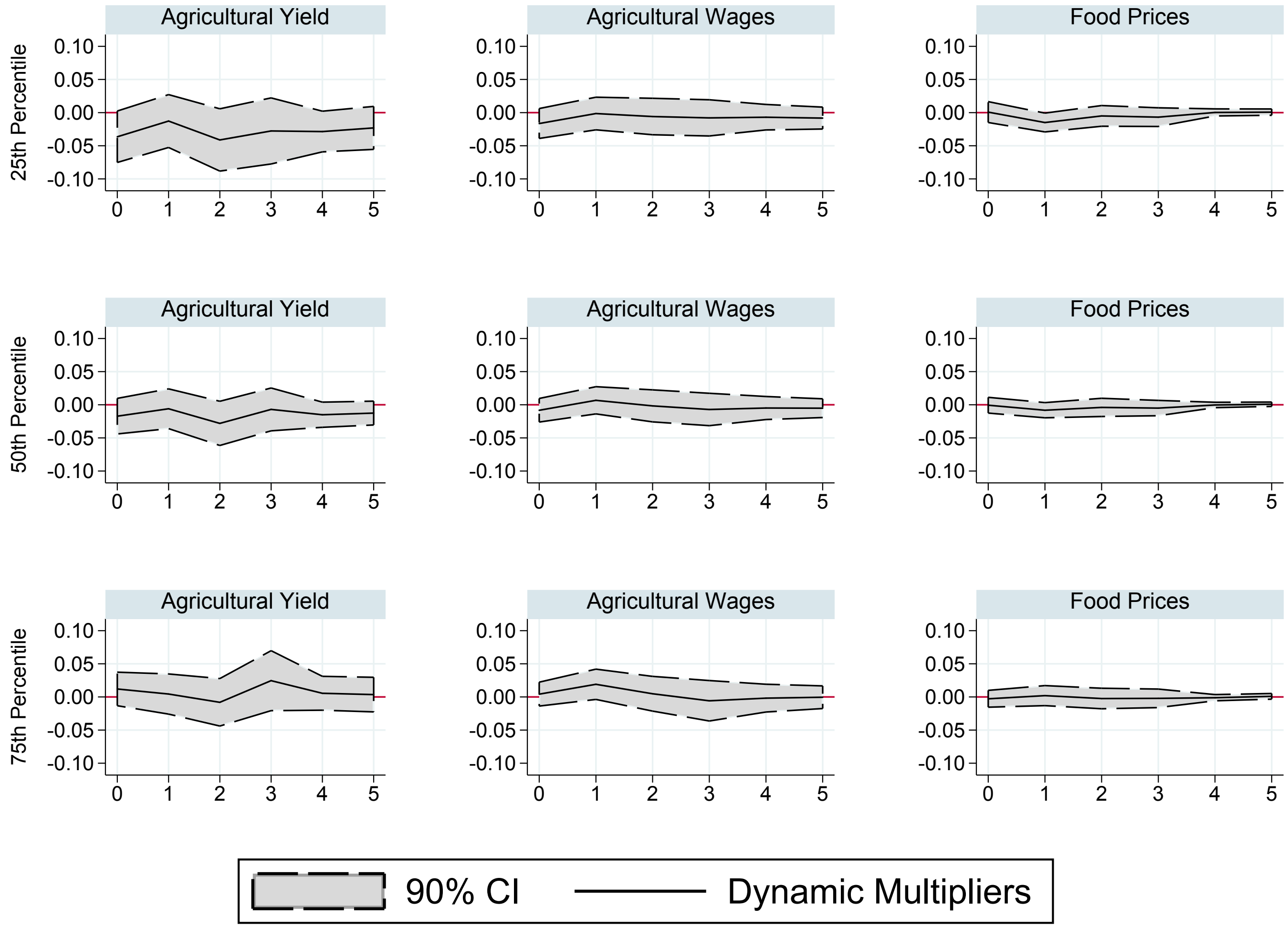


Figure 9: The figure illustrates the impulse responses to a positive variation in overall standardised kharif rainfall of one standard deviation caused by a purely local rainfall shock when overall standardised kharif rainfall is above its mean. The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects are presented for different levels of irrigation. The results are based on 2951 observations at the selected lag-length.

A.10 Response to Positive Regional Rainfall Variation

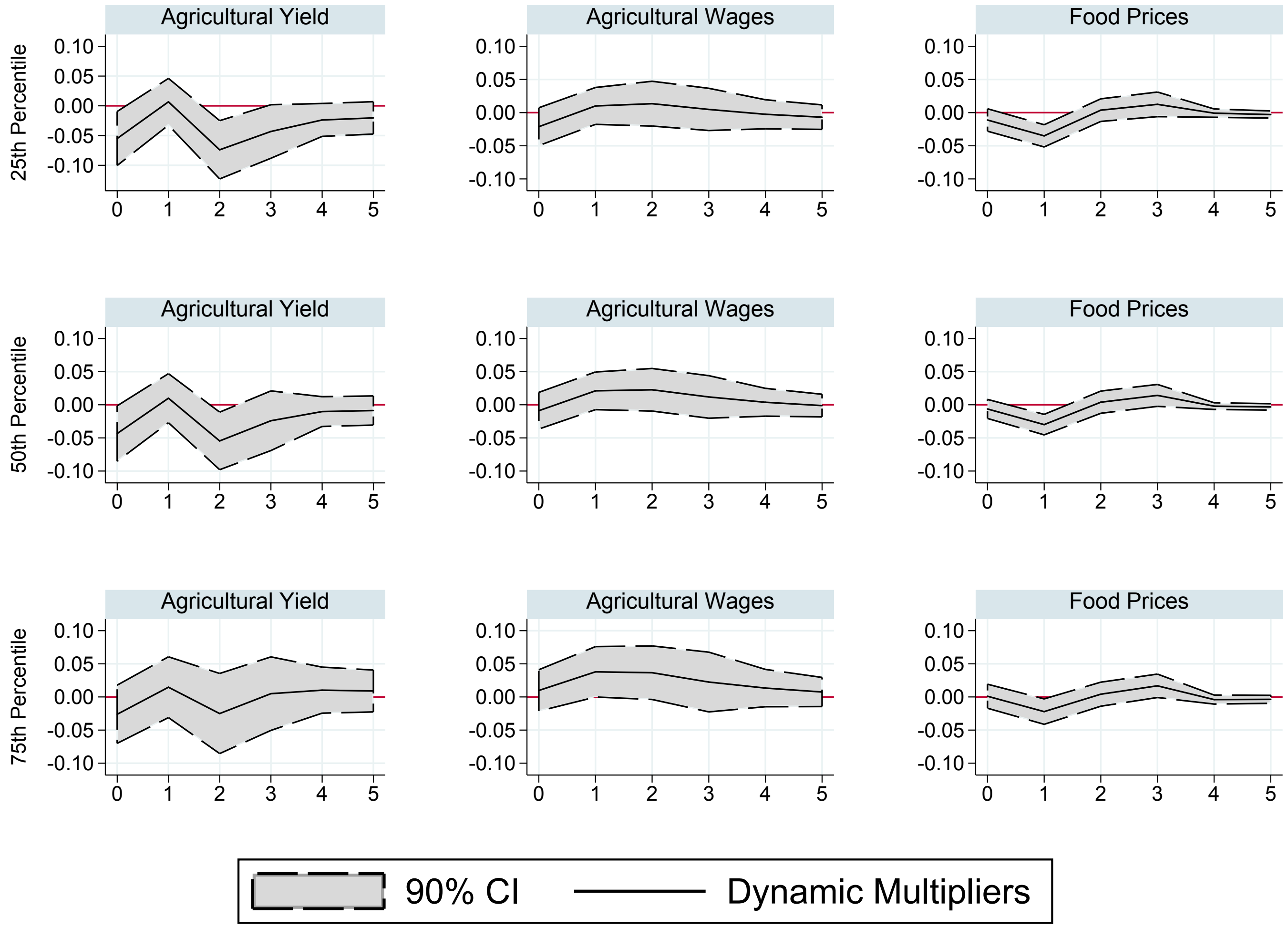


Figure 10: The figure illustrates the impulse responses to a positive variation in overall standardised kharif rainfall of one standard deviation caused by a regional rainfall shock when overall standardised kharif rainfall is above its mean. The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects are presented for different levels of irrigation. The results are based on 2951 observations at the selected lag-length.

A.11 Response of Kharif and Rabi Crops to Positive Regional Rainfall Variation

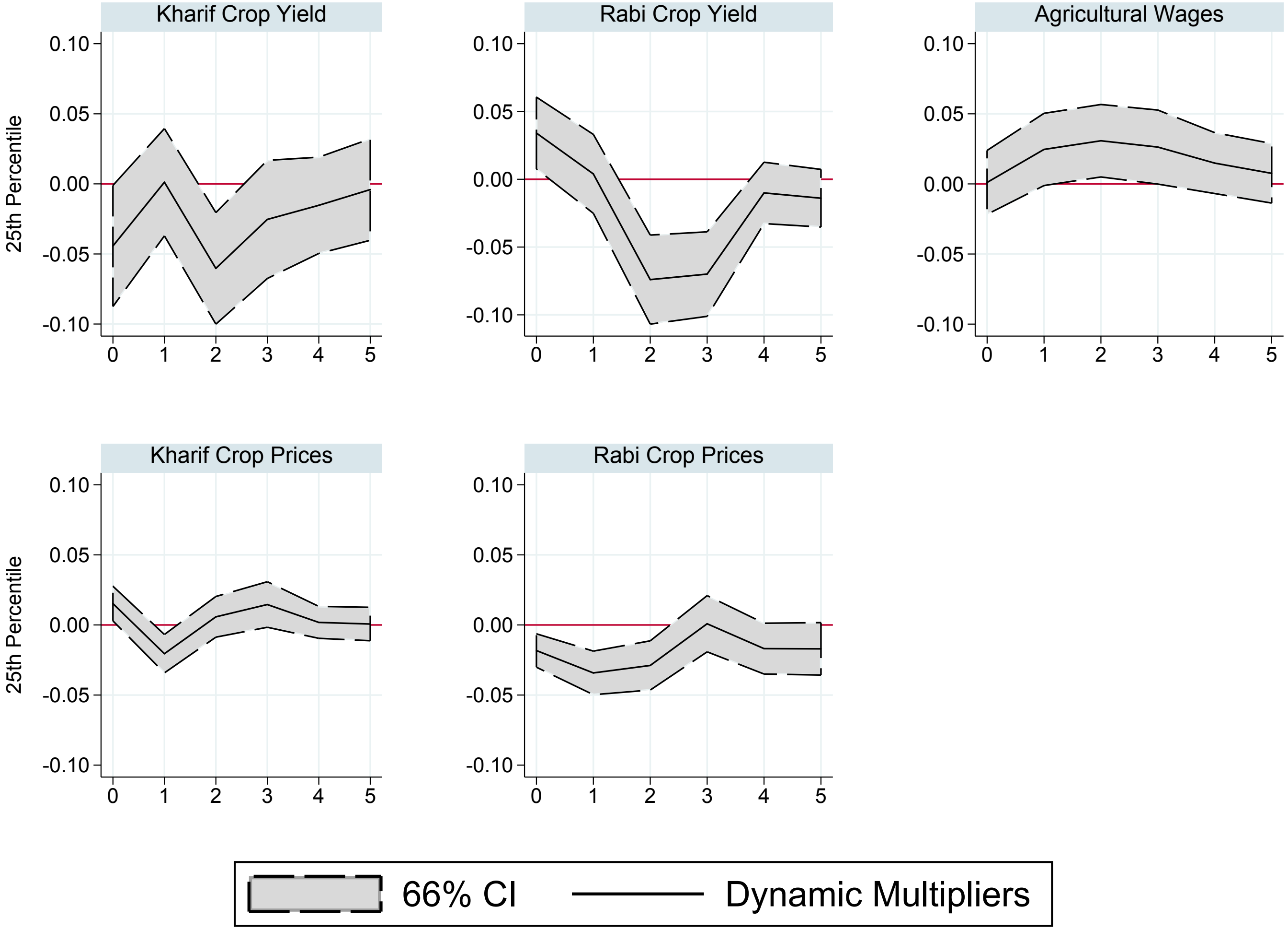


Figure 11: The figure illustrates the impulse responses of kharif crop yield and prices, rabi crop yield and prices, and agricultural wages to a positive variation in overall standardised kharif rainfall of one standard deviation caused by a regional rainfall shock when overall standardised kharif rainfall is above its mean. The number of observations at the selected lag-length is only 1277 due to a high number of missing values for rabi crop yield and prices. For this reason, we adjust the confidence intervals to be at the 66% level.

B Tables

B.1 Summary Statistics

	Mean	Standard Error	Observations
Rainfall Variables:			
Annual Rainfall (in cm)	116.62	67.00	12,089
Monsoon Rainfall (in cm)	98.08	56.66	12,089
Monsoon Season Rainfall SD.	0.00	0.99	12,089
Local Monsoon Rainfall SD.	0.00	0.59	12,089
Regional Monsoon Rainfall SD.	0.00	0.79	12,089
Agricultural Sector Variables:			
Log agricultural yield (ton/km^2)	4.69	0.69	10,643
Log agricultural wage (*Rupee*)	2.44	1.15	8,877
Log price index (*Rupee*/*ton*)	7.66	0.78	8,526
Other Variables:			
Share of irrigated land	0.33	0.25	11,070
Monsoon temperature (demeaned)	0.00	0.46	12,089

Table 1: The table presents descriptive statistics for both, the original variables and the transformed variables used in the baseline specification.

B.2 Rainfall Effects Month-by-Month

	June	July	Aug	Sept	Oct
Panel A: Monthly Standardised Rainfall on Monthly Regional Rainfall					
Coefficient	0.87***	0.84***	0.81***	0.88***	0.91***
Std. Err.	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)
R^2	0.75	0.70	0.65	0.77	0.83
Observations	12,089	12,089	12,089	12,089	12,089
Panel B: Annual Agricultural Yield on Monthly Standardised Rainfall					
Overall Rainfall	0.028***	0.005	0.000	0.042***	0.043***
Std. Err.	(0.004)	(0.004)	(0.004)	(0.004)	(0.004)
within R^2	0.005	0.000	0.000	0.010	0.011
Observations	10,643	10,643	10,643	10,643	10,643
Panel C: as in Panel B, but separately for negative and positive shocks					
Negative Rainfall	0.095***	0.023**	0.071***	0.139***	0.135***
Std. Err.	(0.010)	(0.009)	(0.010)	(0.010)	(0.010)
Positive Rainfall (Dummy)	-0.105***	-0.030**	-0.120***	-0.157***	-0.134***
Std. Err.	(0.014)	(0.013)	(0.014)	(0.014)	(0.015)
within R^2	0.010	0.001	0.007	0.022	0.018
Observations	10,643	10,643	10,643	10,643	10,643

Table 2: The table presents information on the spatial dimension of overall rainfall variation for each month over the kharif season as well as their importance for annual crop yield. Panel A shows the results for univariate regressions of monthly standardised rainfall on monthly regional rainfall. Panel B presents results for univariate regressions of annual agricultural yield on monthly standardised rainfall (both demeaned at the district level). Panel C displays the results when the coefficients are estimated separately for negative and positive rainfall shocks (the impact of positive shocks is given by the sum of the two coefficients). Importantly, we do not control for any time-fixed effects in the regressions, as these would also capture the impact of regional rainfall variation. Robust standard errors are reported in brackets. Stars (*,** ,***) indicate significance at the 10%, 5%, and 1% level, respectively.

B.3 Comparison of Different Rainfall Data Sets

	Baseline	Small Districts	Large Districts	APHRODITE Dataset
Dependent Variable: Same-Year Response of Agricultural Yield				
Panel A: Negative Rainfall Shocks at Low Irrigation				
Local Shock	-0.148***	-0.174***	-0.119**	-0.084**
	(0.033)	(0.039)	(0.055)	(0.037)
Regional Shock	-0.316***	-0.295***	-0.271***	-0.320***
	(0.034)	(0.047)	(0.043)	(0.033)
Observations	2,952	1,503	1,449	2,932
Panel B: Negative Rainfall Shocks at Medium Irrigation				
Local Shock	-0.118***	-0.129***	-0.091***	-0.063**
	(0.025)	(0.031)	(0.032)	(0.027)
Regional Shock	-0.222***	-0.175***	-0.149***	-0.232***
	(0.030)	(0.039)	(0.037)	(0.027)
Observations	2,952	1,503	1,449	2,932
Panel C: Negative Rainfall Shocks at High Irrigation				
Local Shock	-0.073***	-0.077**	-0.049	-0.031
	(0.027)	(0.033)	(0.045)	(0.025)
Regional Shock	-0.079**	-0.083*	0.037	-0.098***
	(0.039)	(0.042)	(0.070)	(0.033)
Observations	2,952	1,503	1,449	2,932

Table 3: The table displays the same-year response of agricultural yield to negative rainfall shocks estimated using our panel VAR model. The column "Baseline" summarises the estimated values for the baseline specification. The column "Small Districts" summarises the estimated values for the subset of those "small" districts where the ratio between the district area and the corresponding region is less than 5%. The column "Large Districts" summarises the estimated values for the subset of those "large" districts where the ration between the district area and the corresponding region is between 5-15%. The last column summarises the estimated values using the APHRODITE Dataset. Robust standard errors are reported in brackets. Stars (*,** ,***) indicate significance at the 10%, 5%, and 1% level, respectively.

C Data Appendix

C.1 Rainfall

The shapefile for 1966 has been created using the publicly available boundary file for Indian districts in 2001 from Census of India (2011), together with information on changes in Indian district boundaries since 1966 from the ICRISAT dataset documentation and Kumar and Somanathan (2015). In case changes to district areas cannot be uniquely attributed to one district, we merge the complete area to the district to which the biggest share of the area would belong to. Based on this, we then construct the buffer areas which cover the district area itself and a 200km area around the district.

The gridded rainfall and air temperature data from Willmott and Matsuura (2012) is available on a monthly basis from 1900-2010 with a resolution of $0.5° \times 0.5°$. We interpolate this grid dataset to a $0.1° \times 0.1°$ grid, so that even the smallest district in the shapefile is at least covering one unique cell. We use the constructed district and buffer area shapefiles to construct average perception in centimetres and air temperature data for the kharif season (June-October).

C.2 Agricultural Yield

Data on the cultivated land area used for individual crops and the corresponding produced crop quantities in the ICRISAT-dataset were originally sourced from the Directorate of Economics and Statistics of the Indian government and the respective states. We use the following major kharif crops: rice, sugar, sorghum, millet, maize and groundnut.

C.3 Agricultural Wages

We use the average male field labour wage (in Rupees per day) for districts from the ICRISAT dataset. The underlying source of the wage data in the ICRISAT dataset is the Directorate of Economics and Statistics of the Indian government.

C.4 Agricultural Prices

Farm harvest price data (measured at the farm gate) in the ICRISAT dataset were originally sourced from the Directorate of Economics and Statistics of the Indian government and the respective states. We use the following set of kharif crops: rice, sugar, sorghum, millet, maize and groundnut. For crop price data, missing observations are a major concern. For this reason, the rice price we use is a combined measure of the paddy and the rice price, where the paddy price was multiplied by the factor of 1.5. This is consistent with the adjustment done in the ICRISAT dataset to combine paddy and rice yield into an overall rice yield measure. Further, remaining missing values for individual log prices are estimated using the median log price at the state level of the respective crop and a set of available log prices of the remaining kharif crops in the same district.

C.5 Irrigation

Data on the irrigated cultivated land area in the ICRISAT dataset were originally sourced from the Directorate of Economics and Statistics of the Indian government and the respective states. The share of irrigated agricultural area is constructed by dividing the irrigated cultivated land area by the total cultivated land area.

D Online Appendix

D.1 Response to Overall Rainfall Variation (pooled results across all levels of irrigation and all spatial dimensions)

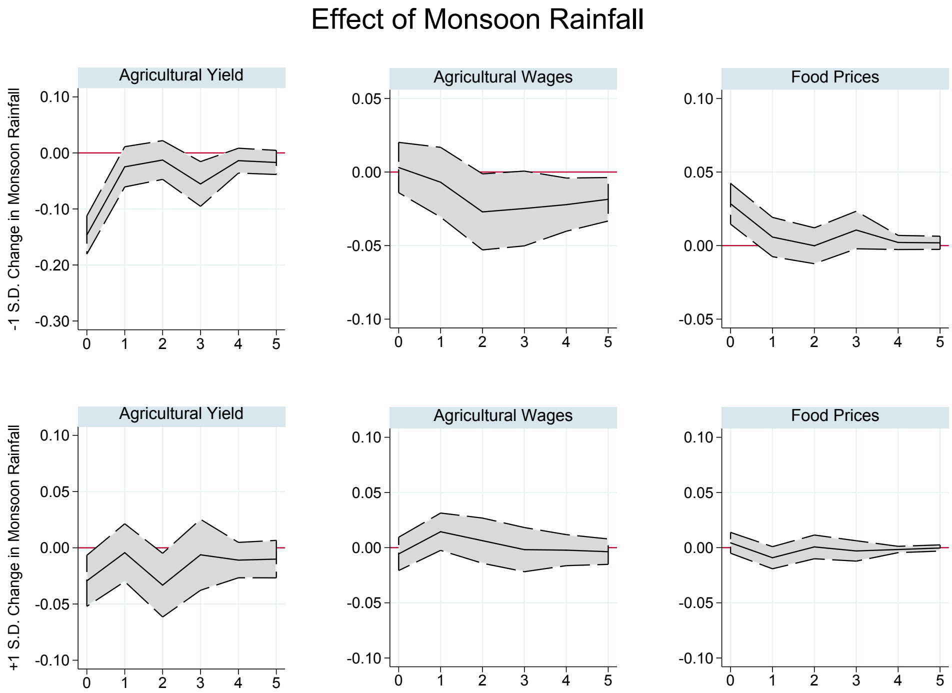


Figure 12: The figure illustrates the impulse responses to a negative (positive) variation in overall standardised kharif rainfall of one standard deviation when overall standardised kharif rainfall is below (above) its mean. The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects are pooled across all levels of irrigation. The results are based on 2951 observations.

D.2 Pooled Results Across all Levels of Irrigation

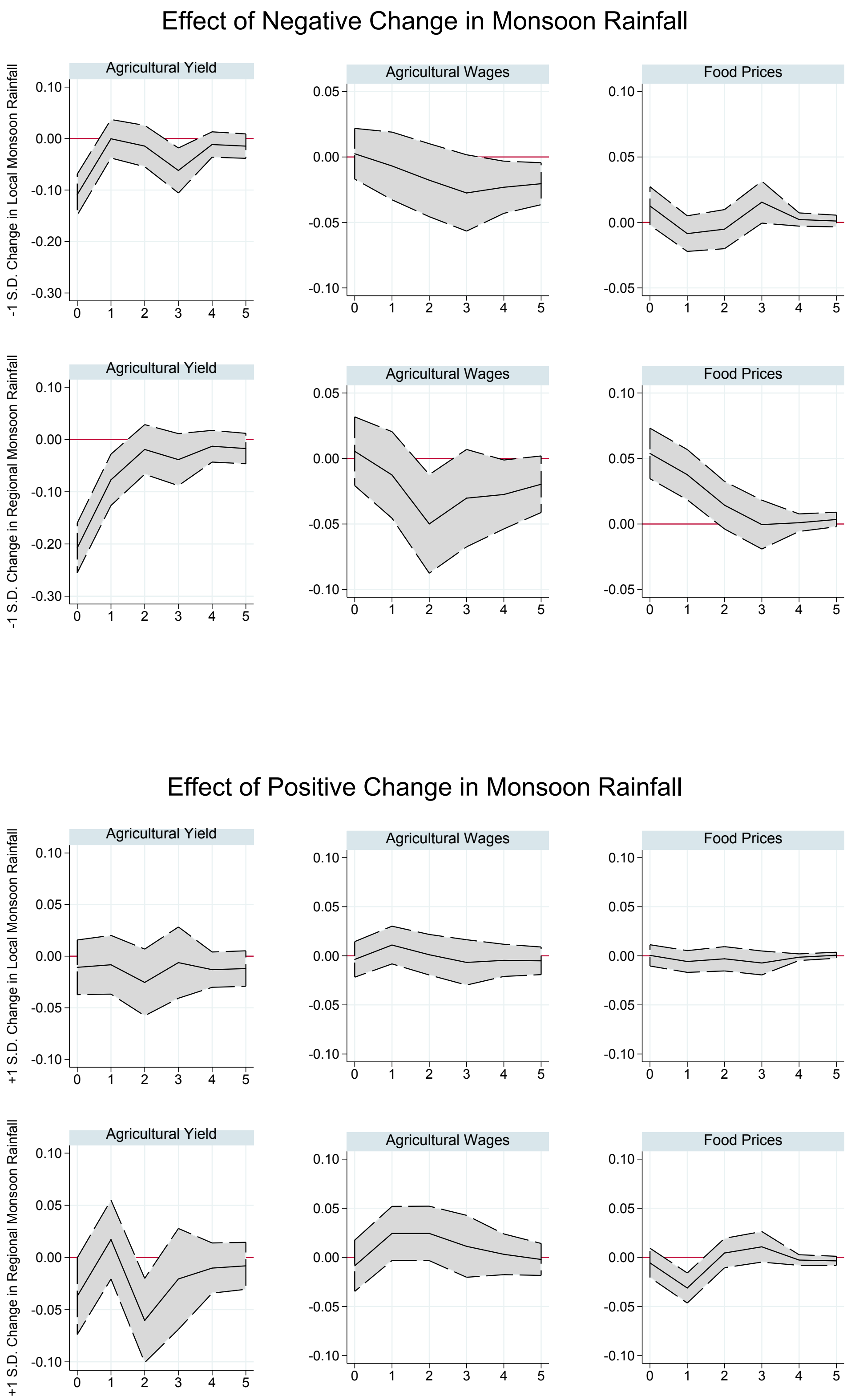


Figure 13: The figure illustrates the impulse responses to a negative (positive) variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock when overall standardised kharif rainfall is below (above) its mean. The black solid line is the point estimate. The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects are pooled across all levels of irrigation. The results are based on 2951 observations.

D.3 Pooled Results Across all Spatial Dimensions

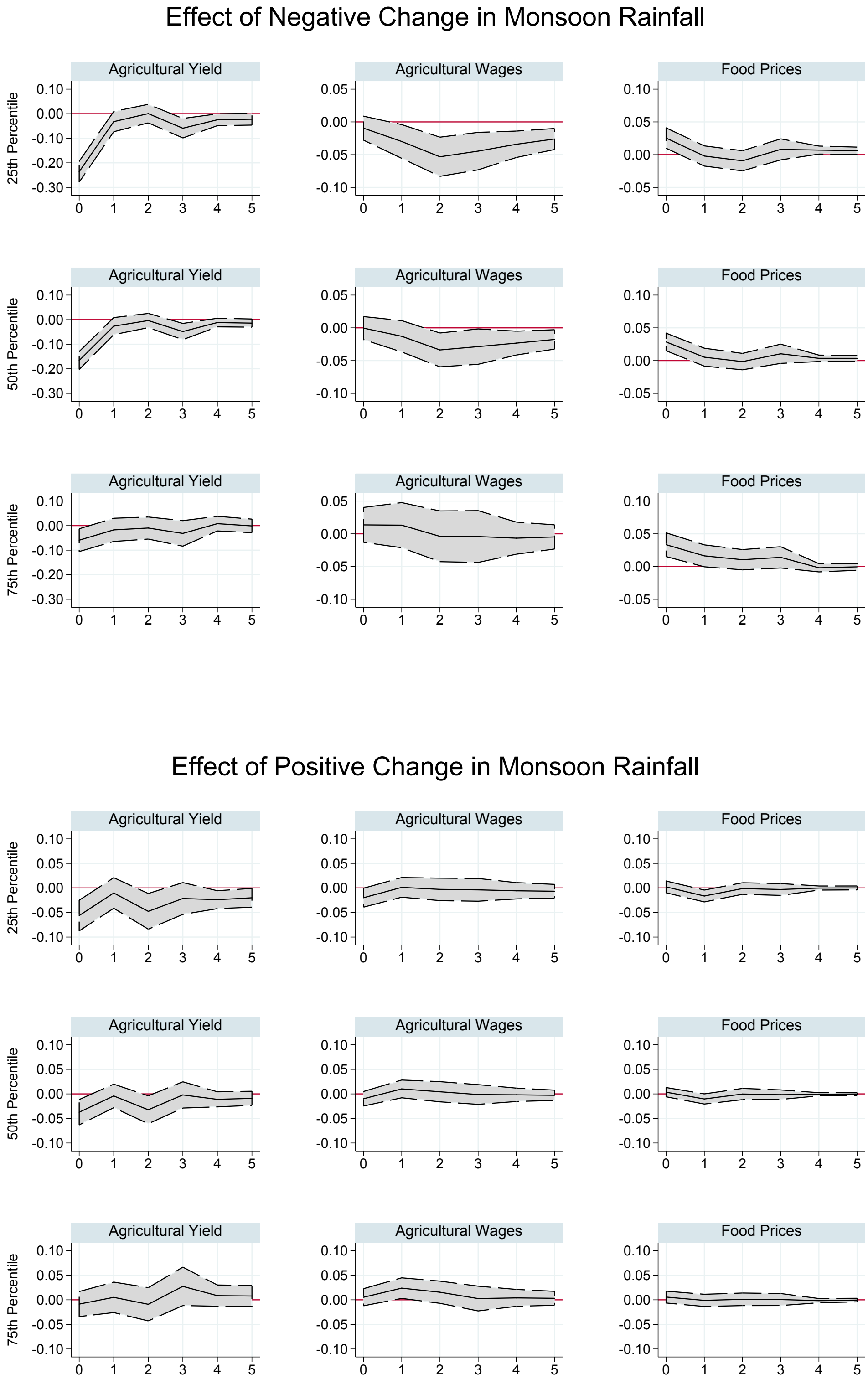


Figure 14: The figure illustrates the impulse responses to a negative (positive) variation in overall standardised kharif rainfall of one standard deviation when overall standardised kharif rainfall is below (above) its mean. The black solid line is the point estimate. The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects are presented for different levels of irrigation. The results are based on 2951 observations.

D.4 Response to Overall Rainfall Variation (irrespective of the sign of the shock)

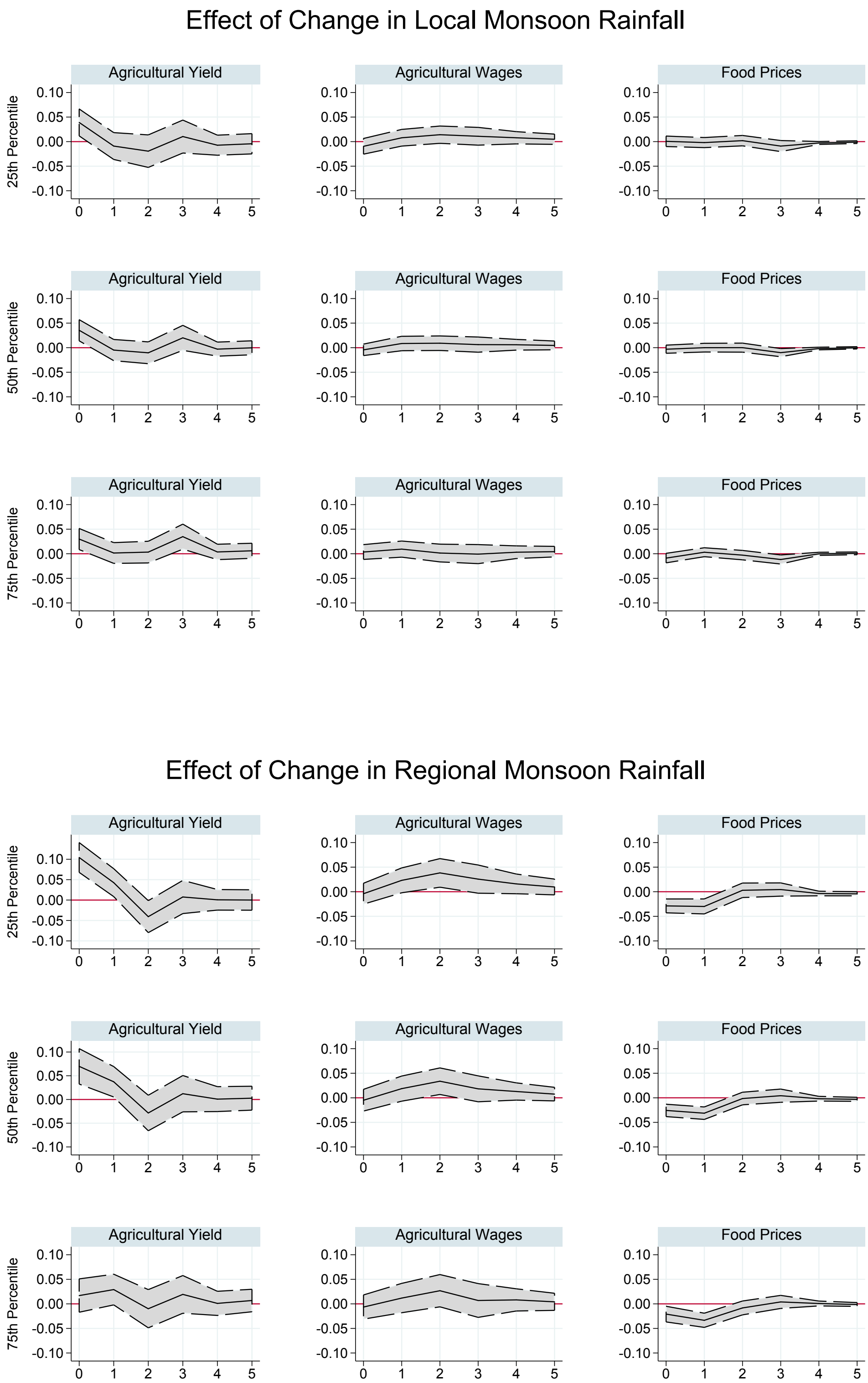


Figure 15: The figure illustrates the impulse responses to a positive variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock. We do not distinguish between above and below normal rainfall. The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects are presented for different levels of irrigation. The results are based on 2951 observations.

D.5 Response to Negative Rainfall Shocks for 5-95% Sample

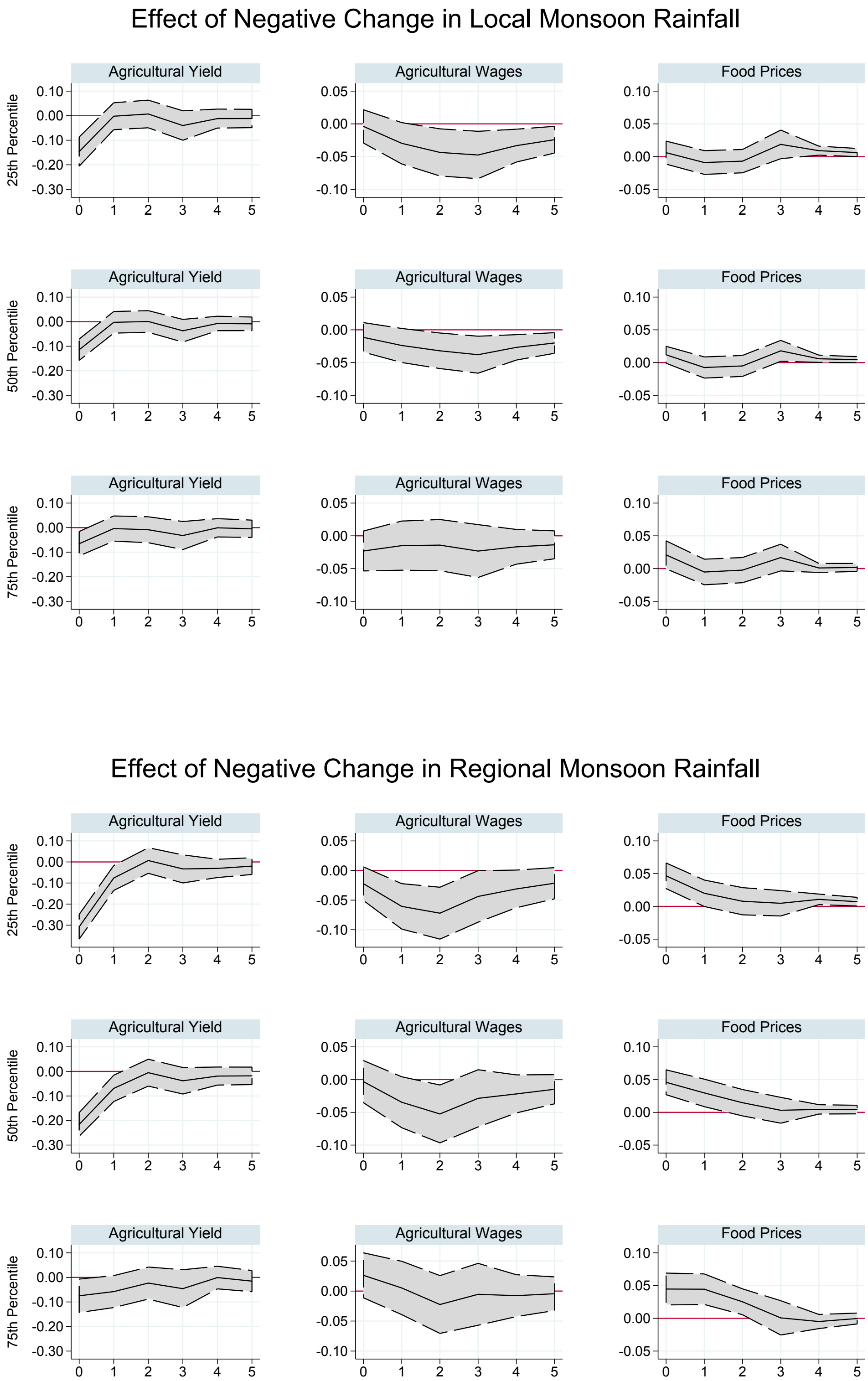


Figure 16: The figure illustrates the impulse responses to a negative variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock when overall standardised kharif rainfall is below its mean. The black solid line is the point estimate. The sample here includes only districts within the 5th-95th percentile of rainfall variation in centimetres. The results are based on 2609 observations.

D.6 Response to Positive Rainfall Shocks for 5-95% Sample

Figure 17: The figure illustrates the impulse responses to a positive variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock when overall standardised kharif rainfall is above its mean. The black solid line is the point estimate. The sample here includes only districts within the 5th-95th percentile of rainfall variation in centimetres. The results are based on 2609 observations.

D.7 Response to Negative Rainfall Shocks for 1967-1991 Sample

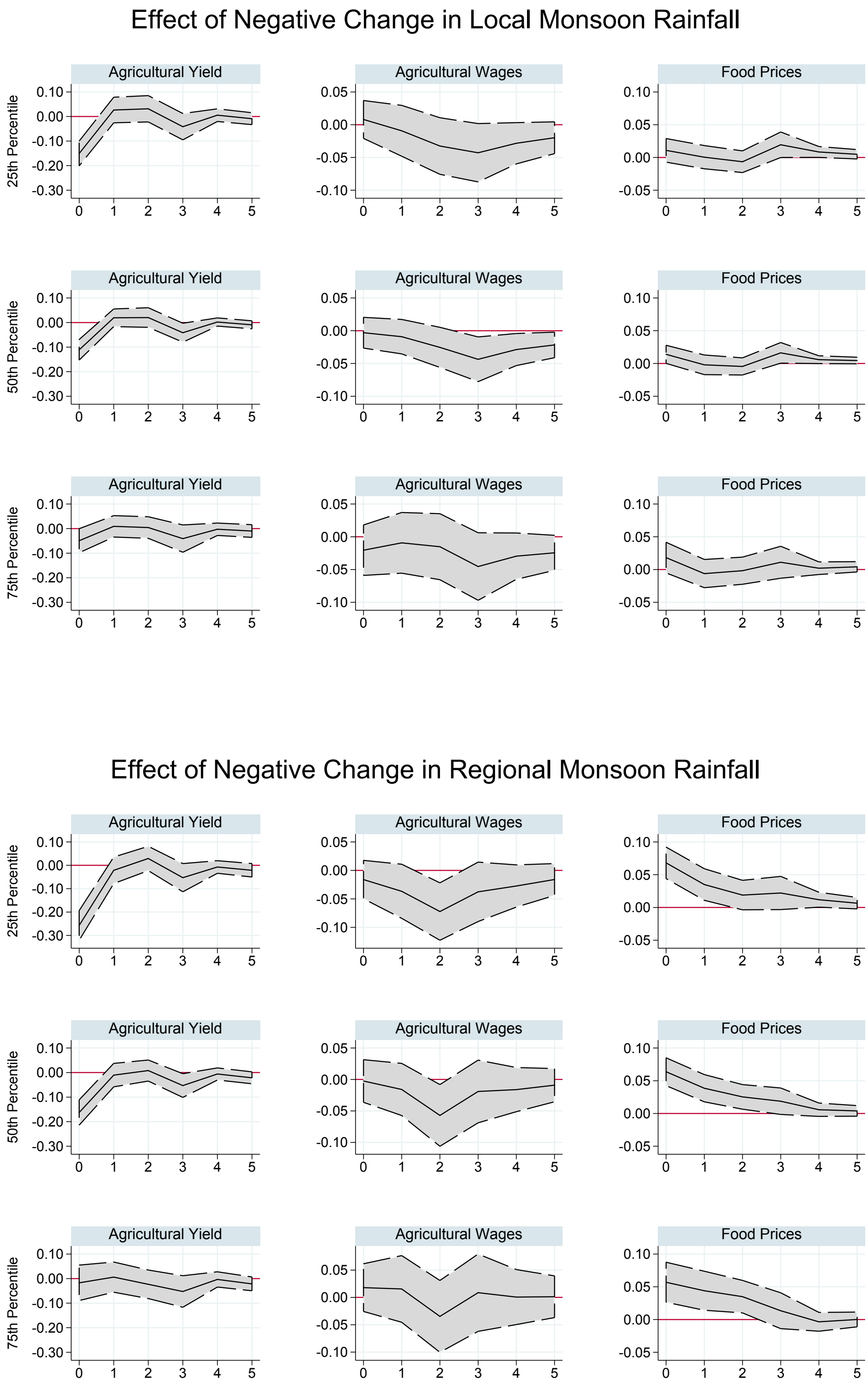


Figure 18: The figure illustrates the impulse responses to a negative variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock when overall standardised kharif rainfall is below its mean. The black solid line is the point estimate. The sample here includes only the years 1967-1991. The results are based on 2207 observations.

D.8 Response to Positive Rainfall Shocks for 1967-1991 Sample

Figure 19: The figure illustrates the impulse responses to a positive variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock when overall standardised kharif rainfall is above its mean. The black solid line is the point estimate. The sample here includes only the years 1967-1991. The results are based on 2207 observations.

D.9 Response to Negative Rainfall Shocks for 1981-2005 Sample

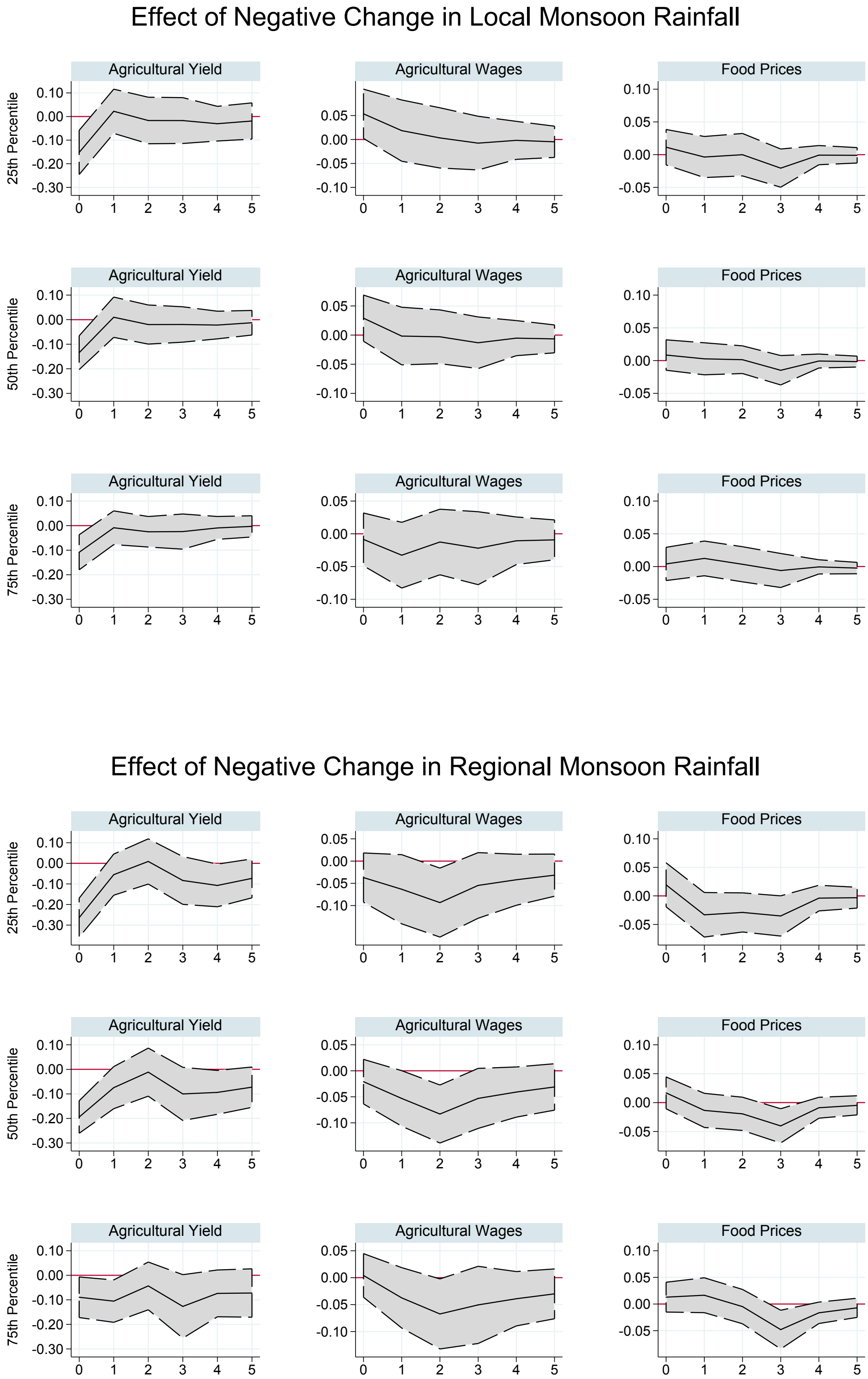


Figure 20: The figure illustrates the impulse responses to a negative variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock when overall standardised kharif rainfall is below its mean. The black solid line is the point estimate. The sample here includes only the years 1981-2005. The results are based on 1413 observations.

D.10 Response to Positive Rainfall Shocks for 1981-2005 Sample

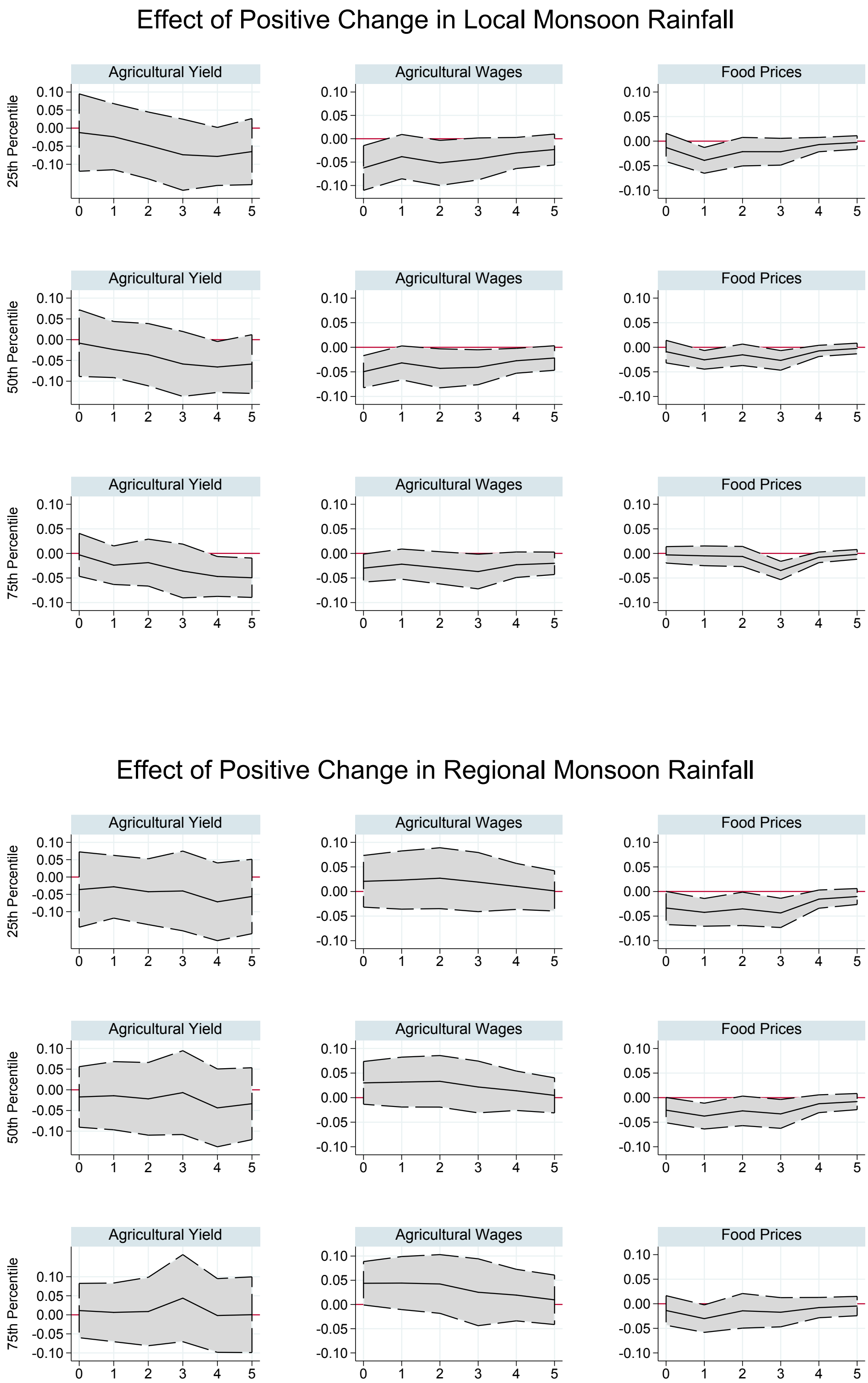
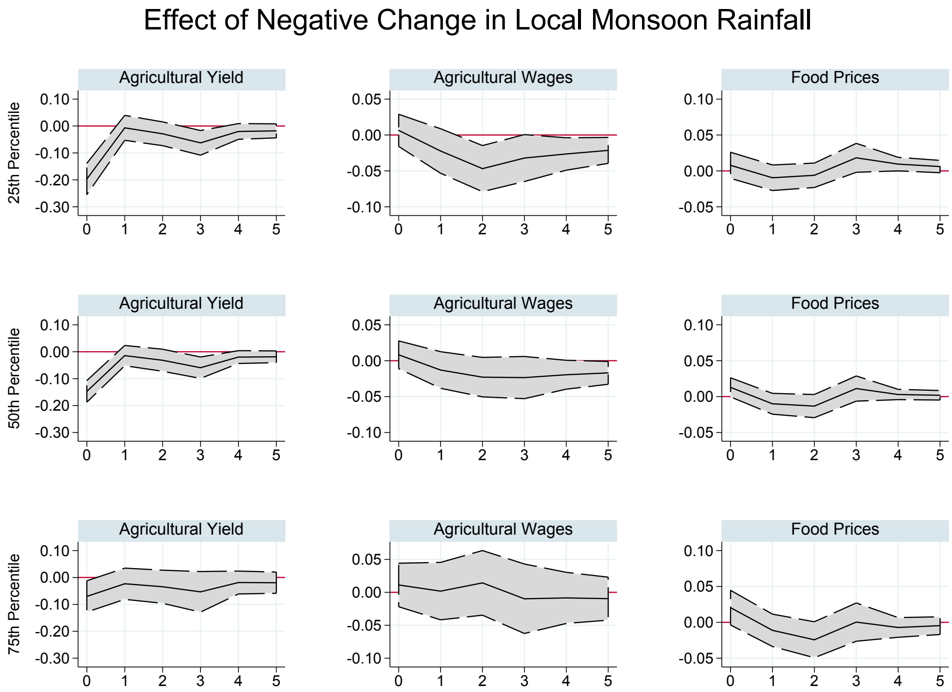


Figure 21: The figure illustrates the impulse responses to a positive variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock when overall standardised kharif rainfall is above its mean. The black solid line is the point estimate. The sample here includes only the years 1981-2005. The results are based on 1413 observations.

D.11 Response to Negative Rainfall Shocks for Southern & Eastern States



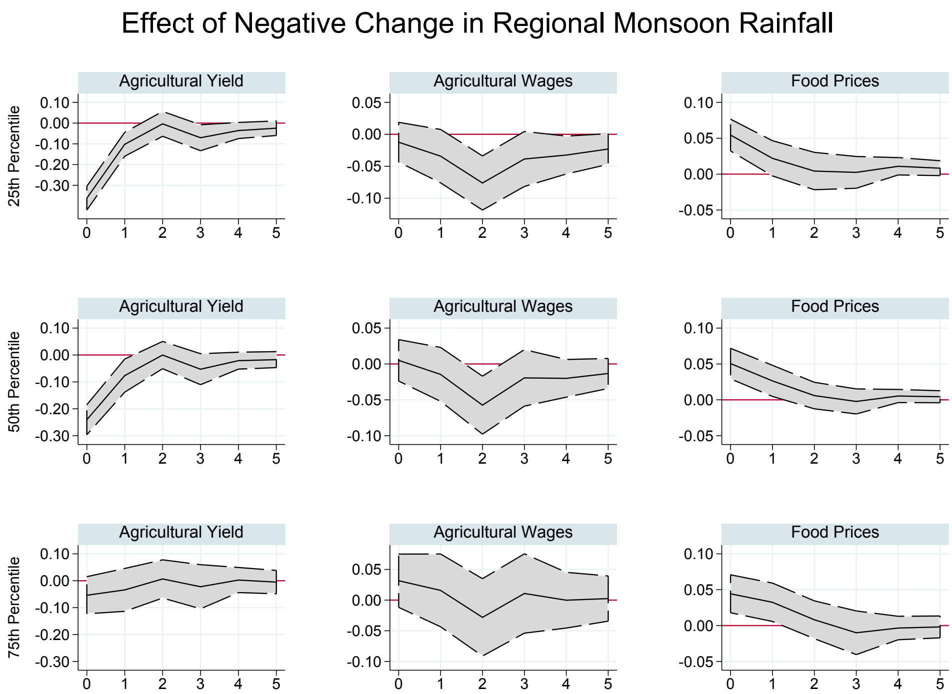
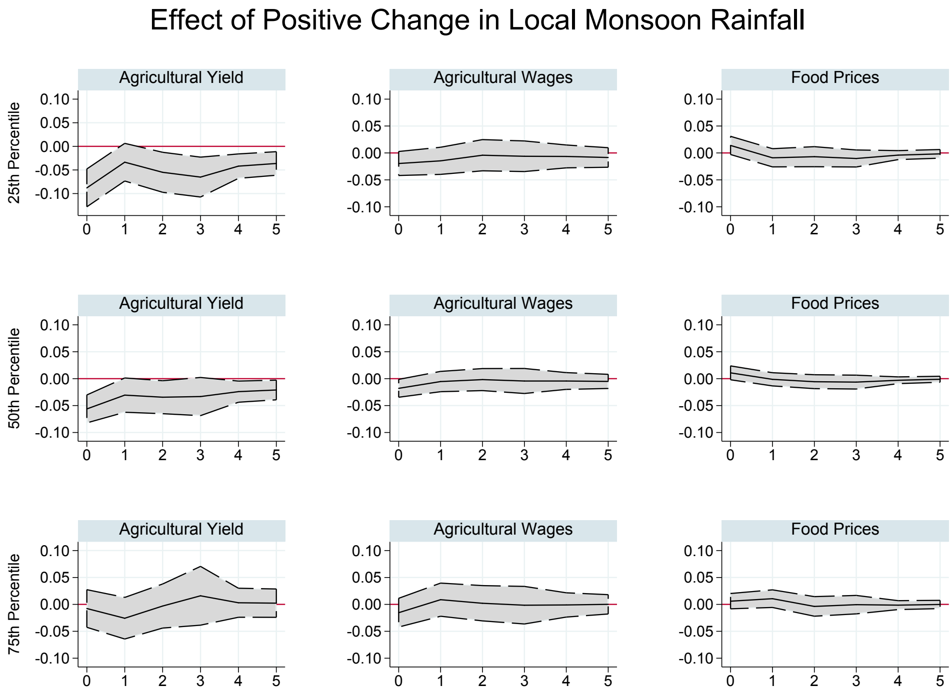


Figure 22: The figure illustrates the impulse responses to a negative variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock when overall standardised kharif rainfall is below its mean. The black solid line is the point estimate. The sample here includes only states in the south and east of India, where monsoon rainfall arrives usually before the 10-15th of June. The results are based on 2257 observations.

D.12 Response to Positive Rainfall Shocks for Southern & Eastern States



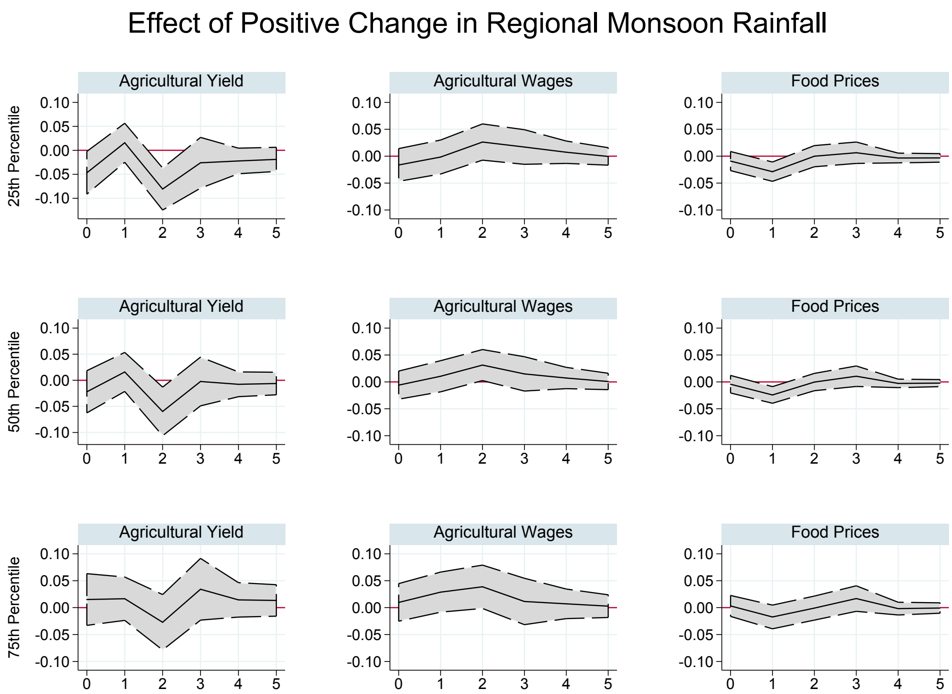


Figure 23: The figure illustrates the impulse responses to a positive variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock when overall standardised kharif rainfall is above its mean. The black solid line is the point estimate. The sample here includes only states in the south and east of India, where monsoon rainfall arrives usually before the 10-15th of June. The results are based on 2257 observations.

D.13 Response to Negative Rainfall Shocks for Northern & Western States

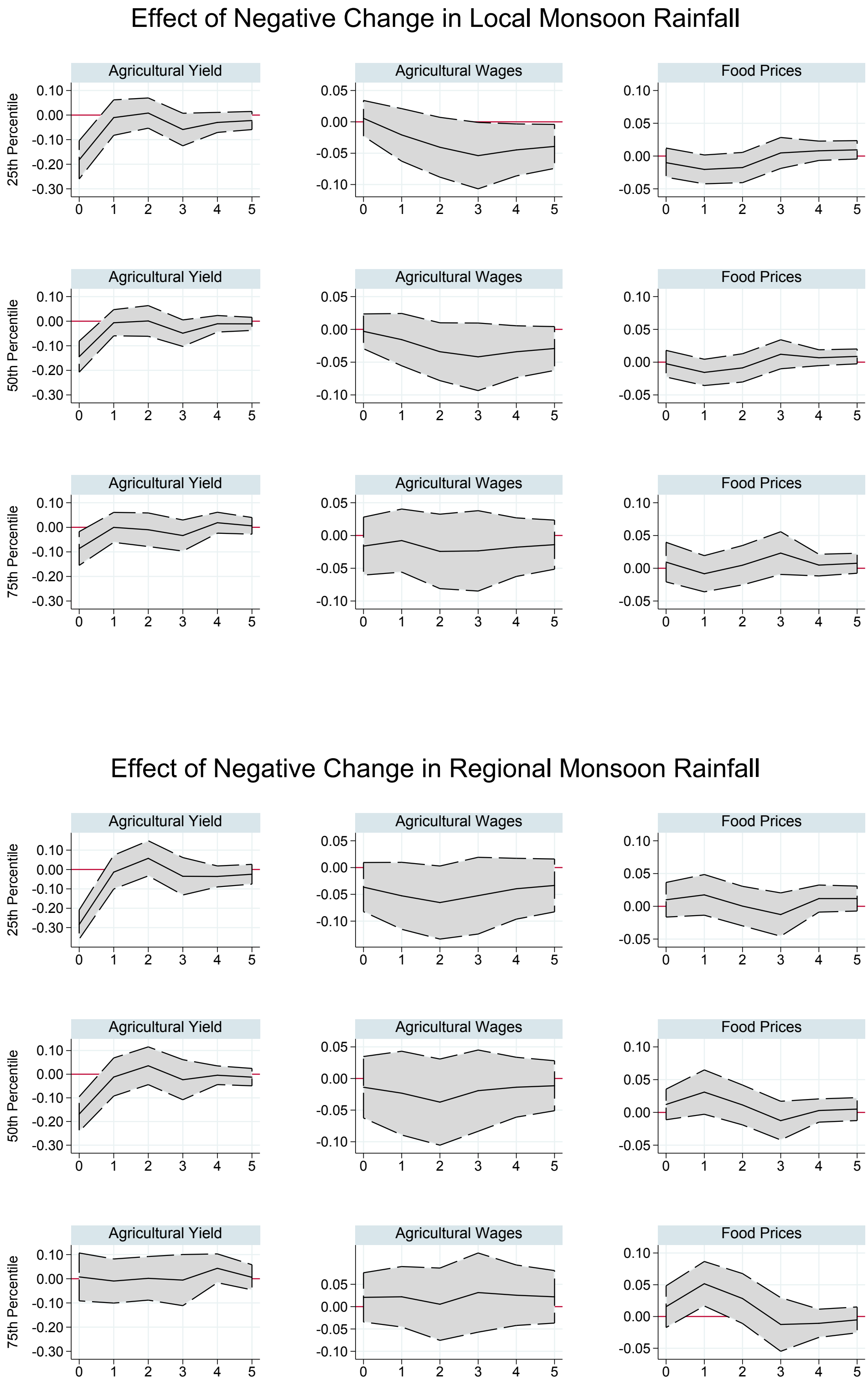


Figure 24: The figure illustrates the impulse responses to a negative variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock when overall standardised kharif rainfall is below its mean. The black solid line is the point estimate. The sample here includes only states in the north and west of India, where monsoon rainfall arrives usually after the 10-15th of June. The results are based on 1766 observations.

D.14 Response to Positive Rainfall Shocks for Northern & Western States

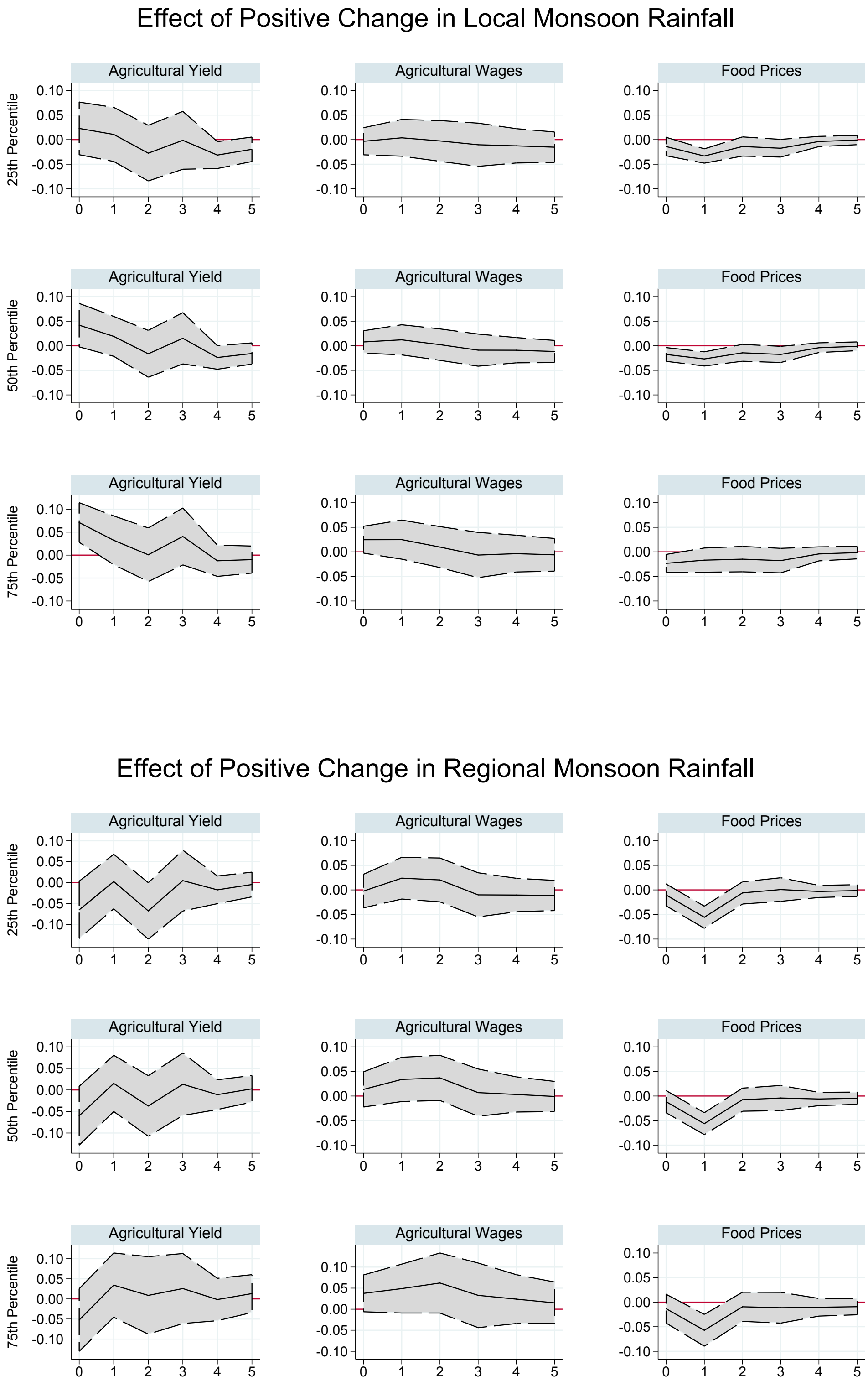


Figure 25: The figure illustrates the impulse responses to a positive variation in overall standardised kharif rainfall of one standard deviation caused by a purely local/regional rainfall shock when overall standardised kharif rainfall is above its mean. The black solid line is the point estimate. The sample here includes only states in the north and west of India, where monsoon rainfall arrives usually after the 10-15th of June. The results are based on 1766 observations.