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 output, 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 output 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.

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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% ..."*
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> — 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 & Rush 2011). Despite huge productivity advances, mainly due to the introduction of high-yield seeds, the increased use of fertilizers, 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 et al. 1998, Himanshu 2007, Iyengar & Viswanathan 2011). The most important source of uncertainty in the Indian agricultural sector are variations in the amount of monsoon rainfall (Coffey et al. 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. We thus take into account that farmers adjust their crop portfolio to differences in mean and variance of monsoon rainfall across districts in India. 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, following Lahiri & Roy (1985) and Gadgil & Gadgil (2006), we distinguish between negative (draughts) and positive (excessive) rainfall shocks. To quantify the effects of rainfall variations on agricultural output, 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. 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 lead to an enormous decline in local agricultural output, which is about twice as large as after a local drought. In either case, the size of the short-lived drop in local agricultural output depends on the local extent of irrigation. After a regional drought, the drop in local agricultural output 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 output and 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 stabilize food prices when droughts are limited to certain districts (*ii*) in the labour market, the arbitrage mechanism through migration is substantially weaker.[1] 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 & Shariff 2004 and De Janvry & 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 output, 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 output, but may gain from the medium-term rise in prices for agricultural output 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 et al. 2006 and Christensen et al. 2007) will likely exert adverse effects (see also Guiteras 2009).

Among the previous literature that has attempted to quantify the consequences of agricultural productivity shocks on the livelihoods of the poor so far (see e.g. Mooley & Parthasarathy 1982, Adams 1989, Paxson 1992, Rosenzweig & Wolpin 1993), 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 output, wages and food prices (*ii*) we distinguish between positive and negative monsoon rainfall shocks to account 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.

[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 & 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 & Stark 1989; Rosenzweig & Wolpin 1993; Dercon 2002; or Aragón et al. 2018).

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

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 output 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 output 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:

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

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 dividing the irrigated cultivated land area by the total cultivated land area.

Furthermore, to identify the effects of exogenous rainfall variations, we first standardize summer monsoon rainfall at the district level based on gridded monthly rainfall data from Willmott & Matsuura (2012). More precisely, for each district, we subtract mean summer

[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 & Udry (2014) find that this act helped to stabilize 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.

monsoon rainfall (in centimetres) from actual summer monsoon rainfall and then divide the difference by the corresponding standard deviation:[7]

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

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. 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 raster).[8] Third, we regress district-wise standardised rainfall on region-wise standardised rainfall:

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

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). 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. The resulting contribution of regional (local) rainfall shocks to the variance in overall standardized rainfall is 64% (36%). Table 1 provides summary statistics for the key variables of interest. More details can be found in Appendix C.

2.2 Data Description

Monsoon rainfall in the kharif season is a crucial determinant of agricultural output in India (Coffey et al. 2015). To illustrate its variability, Figure 3 depicts a histogram of standardized monsoon rainfall at the district level (see Equation 3) as well as the corresponding normal distribution. We observe that the distribution of standardized 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.[9] Given the good fit of the normal distribution, positive/negative variations of more than one standard

[7]This rainfall measure is closely related to the "Standardized Precipitation Index" (McKee et al. 1993) developed to classify the severity of droughts (where a value of -1 represents a moderate drought).

[8]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 stylized 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.

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

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 output 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.[10] The LOWESS curve indicates that negative deviations in standardized rainfall reduce agricultural output substantially, while rainfall above the district-mean has only a small negative impact on agricultural output. This pattern is also well captured by a linear regression with a break point at mean district-wise rainfall.[11] 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 output 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 of irrigation. 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 output appears to change little at higher levels of irrigation. In our estimation strategy, we therefore control for the interaction effects between rainfall and irrigation.

Our paper aims at understanding 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 output, 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 standardized 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 output (the main agricultural crop).[12] However, in the year after the shock, rice output 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 observed degree of wage rigidity 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

[10] 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).

[11] 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 conceptualized in the "FAO water production function" (see e.g. Steduto et al. 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 standardized rainfall. Guiteras (2009), for instance, captures the non-linearity by including a squared term for rainfall.

[12] Given that only very few negative monsoon rainfall shocks meet these criteria, we use rice output and prices instead of the composite measures to maximize the available sample size.

hand, in the year directly after 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 output, wages and prices in the Indian agricultural sector, as well as the interdependencies between these variables.[13] For this purpose, we estimate a panel VAR based on data from 310 Indian districts (Holtz-Eakin et al. 1988; Abrigo & Love 2016).[14] To control for unobserved heterogeneity at the district level, we apply the Helmert transformation (see Nickell 1981; Arellano & Bover 1995; Balestra & Krishnakumar 2008).[15] 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 et al. (2003), which have been selected following Hall & 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 et al. 2002).[16] This means that the dataset meets the two major requirements for the use of a panel VAR: (i) comparability and (ii) stationarity (Neumann et al. 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 & Lu (2001) lag-length selection criterion, we set out to estimate the following third order VAR model:[17]

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

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

[14] 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 & Ciccarelli (2013).

[15] 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 & Bond 1991; Arellano & Bover 1995; Blundell & Bond 1998; Judson & Owen 1999; Love & Zicchino 2006).

[16] For the irrigation-share variable, only the unit-root test of Im et al. (2003) concludes that panels are stationary. 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 endogenous variable, but the pattern of some impulse responses appears less smooth.

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

where $Y_{n,t}$ is a vector containing the following four endogenous variables: log agricultural output, $Output_{n,t}$, 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. 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.[18] 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 output, 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).

[18] 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.

4.1 Baseline Specification

Negative local rainfall shock: Figure 7 shows the effects of a negative local rainfall shock if overall standardized rainfall is below its mean. We show the effects of a one standard deviation reduction in monsoon rainfall 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 output are mitigated by irrigation: the size of the negative spike shrinks (in absolute terms) from -14% at the 25% percentile of irrigation to -11% at the median level of irrigation and to -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.[19] At the first quartile of irrigation, the maximum impact of -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 share-croppers, while agricultural labourers suffer only little.[20,21] 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 do not respond significantly to a local reduction in monsoon rainfall — irrespective of the share of irrigated land. This likely reflects the accommodating effects of intra-regional arbitrage trading, which avoids 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.[22]

Negative regional rainfall shock: Figure 8 presents the responses of agricultural output, wages and food prices to a regional decline in monsoon rainfall. This corresponds to a general reduction of rainfall in the district itself and the surrounding area with a radius of 200km. We note that the effects on agricultural output are now substantially larger, particularly at low levels of irrigation. Again, the effects on agricultural output are short-lived, having nearly

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

[20] 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.

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

[22] 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.

completely disappeared in the following year and being no longer significant. Regional shocks decrease agricultural output more severely than local shocks, likely because regional shocks reduce the availability of water more strongly, given their larger impact on the hydrological cycle in the district (e.g. through surface runoffs and groundwater flows).

Moreover, we observe that the stronger response in agricultural output translates also into a 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.[23] 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 output 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 about 5% 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 output 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). 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 local rainfall shock of one standard deviation. We observe that such a shock exerts no significant effects: neither on agricultural output, nor on wages or food prices at any horizon. This implies that the effects of local rainfall variations are strongly

[23]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.

asymmetric.[24] 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 output, wages and food prices to a one standard deviation increase in regional rainfall. Unlike in the case of positive local shocks, agricultural output 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 -3.4% (-2.7%) 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 reduces harvest prices of substitutable kharif crops in the following year. Indeed, Figure 11 illustrates that the response of rabi crop output (prices) to a positive regional rainfall shock is positive (negative).[25] The (renewed) decline in kharif and rabi output 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.[26]

Temperature: Figure 12 presents the responses to an increase in temperature during the monsoon season.[27] There is no significant effect on agricultural output or wages, but food prices seem to decline following a particularly warm monsoon period. Given the unchanged response of agricultural output, this likely reflects better conditions for post-harvest drying (Bonazzil et al. 1997), which facilitates storage and consequently reduces prices.

[24] 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 & Roy (1985) and Gadgil & Gadgil (2006). These papers, however, have a different focus than ours in terms of selected variables and the geographical level of interest.

[25] To generate Figure 11, we additionally include agricultural output 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 output 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 & Kurian 2016). For this reason, the fact that the negative response of kharif output in Figure 11 is insignificant does not establish a major concern.

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

[27] We also tested a set of additional potentially relevant climatic controls, i.e., standardized rainfall in June, October and during winter (November-February) as well as winter temperature. We find that the effects of monsoon rainfall shocks remain nearly identical.

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 output and the price they 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 output. 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 output. 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.[28]

Our results thus relate to the work of Sen (1981), according to which famines cannot easily be explained by reductions in agricultural output 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.[29] 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 (Devereux 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 et al. 1998, Christensen et al. 2007, Kripalani

[28] 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.

[29] 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).

et al. 2007), this development will likely affect the livelihoods of the poorest in a severe way, particularly of agricultural labourers.[30] We also find that irrigation mitigates the decline in agricultural output and wages (but hardly the rise in food prices). However, 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 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.[31] 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 13). As expected, the size of the responses in agricultural output 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 tighter confidence bands) and the response of food prices. The main conclusion from this exercise is that persistent impulse responses are a robust feature of the data, even if the extent of irrigation and the spatial dimension of rainfalls shocks are not accounted for.

Similarly, Figure 14 shows the impulse responses when we control for the spatial dimension of the rainfall shock, but not for the level of irrigation, whereas Figure 15 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 two findings: (*i*) Both, agricultural output and 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. Overall, these results indicate that arbitrage trading at the regional level helps to stabilize food prices when droughts are limited to certain districts. In the labour market, however, the arbitrage mechanism through migration seems substantially weaker.

Figure 16 depicts the impulse responses of agricultural output, 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). Thus, the

[30] 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.

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

results seem to suggest that additional rainfall always exerts a positive effect on agricultural output 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 output 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 17 shows that the responses of agricultural output 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 18 depicts that also the responses to (both, local and regional) positive rainfall shocks are very robust to the exclusion of outlier districts.[32]

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 19 and 20), while the late sub-sample ranges from 1981-2005 (see Figures 21 and 22).[33] 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),[34] which helped to increase supra-regional trade and, thus, reduced supra-regional price gaps.[35] In addition, we find that agricultural output 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 23 and 24) with the estimated impulse responses for districts in northern and western parts of

[32] 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).

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

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

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

India were the monsoon arrives usually after the 10-15th of June (see Figures 25 and 26). We find that 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 output 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 output (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 output, 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 lead to an enormous decline in local agricultural output, which is about twice as large as after a local drought. In either case, the size of the short-lived drop in local agricultural output depends on the local extent of irrigation. After a regional drought, the drop in local agricultural output 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 output and 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 stabilize 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 & Shariff 2004 and De Janvry & 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 output, 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 output, but may gain from the medium-term rise in prices for agricultural output 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

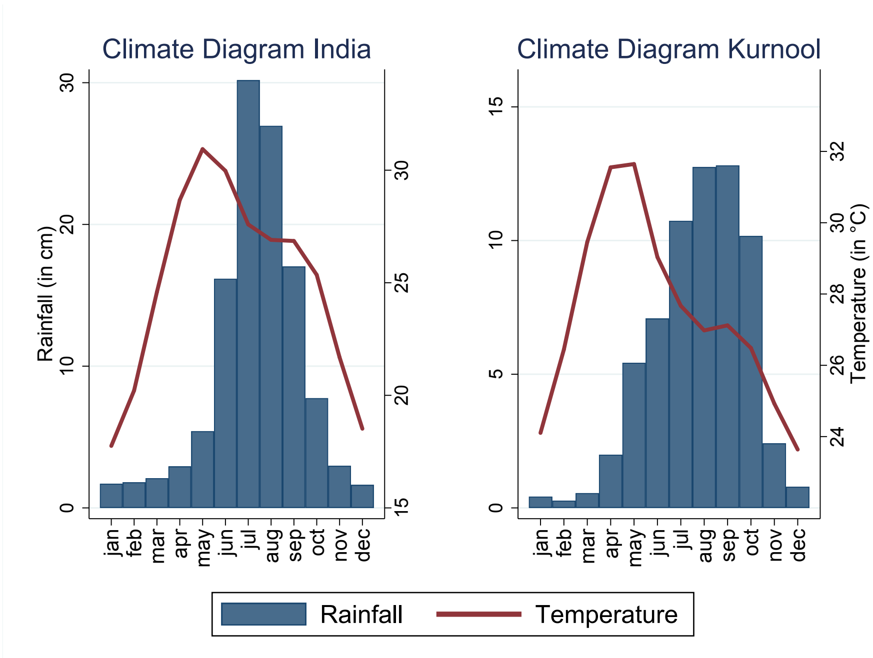


Figure 1: The figure depicts the climate diagram over the period 1967-2005 for entire India (on the left) and the Kurnool district in Andhra Pradesh (on the right). The data source is Willmott & Matsuura (2012).

A.2 Buffer Area Illustration

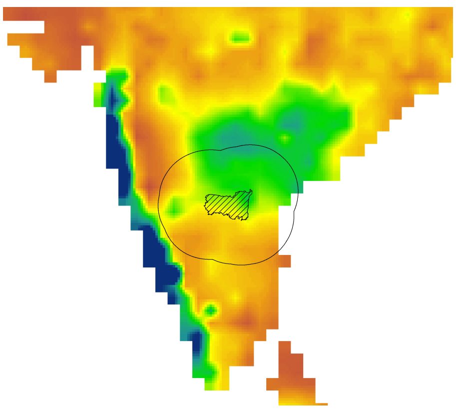


Figure 2: The figure depicts the Kurnool district in the state of Andhra Pradesh with an area of 17,626 km^2 (shaded area). The average size of an Indian district is about 10,000 km^2. The area surrounding the district is the 200km buffer area. The areas are calculated using a projected coordinate system — 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

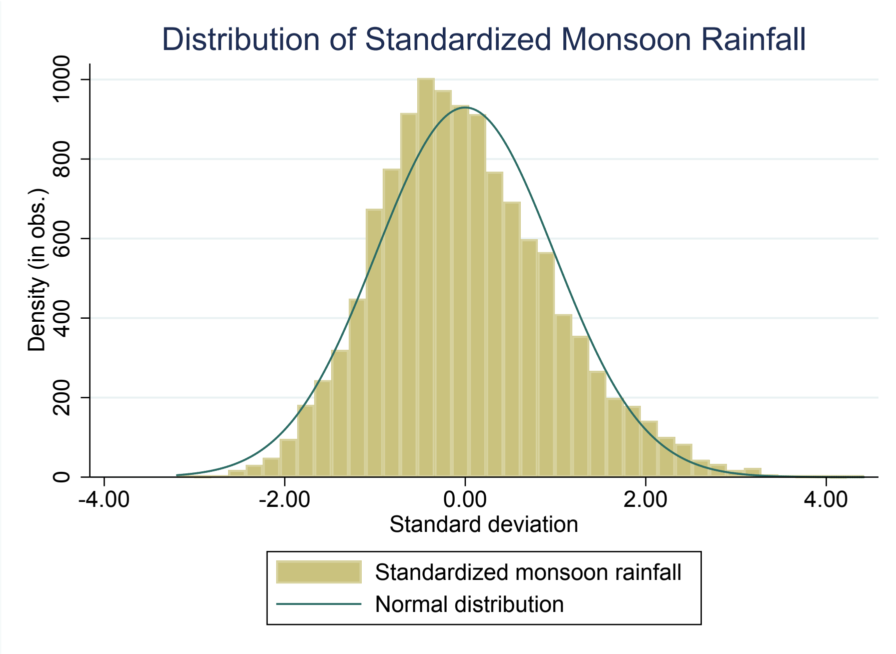


Figure 3: The figure depicts the standard normal distribution and the distribution of standardized monsoon rainfall as defined in Equation 3.

A.4 Rainfall Variation and Agricultural Output Growth

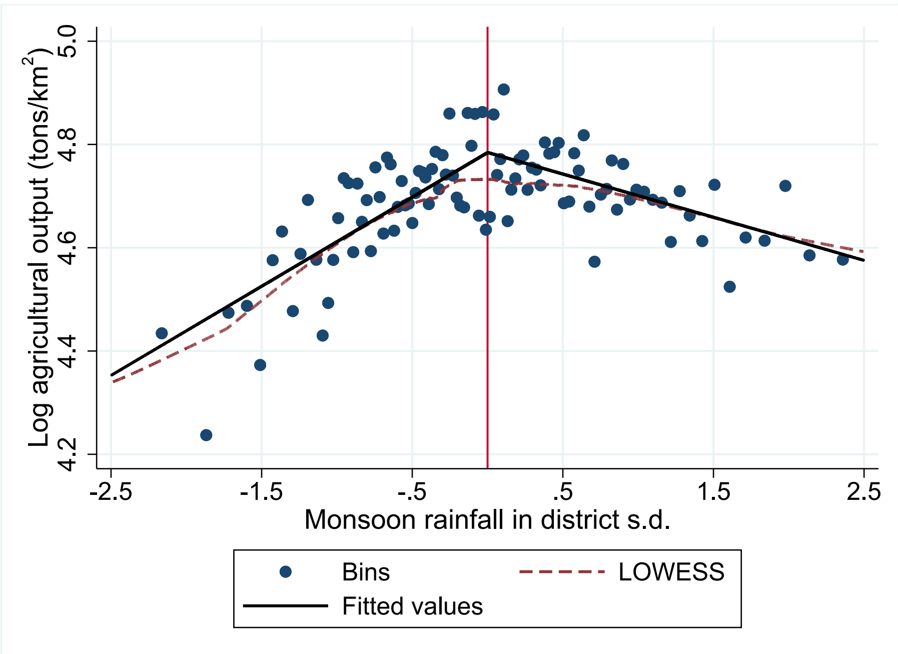


Figure 4: The figure presents a binned scatterplot (100 bins with $\approx$ 104 observations each) for variations in monsoon rainfall and log agricultural output. To outline the effect of monsoon rainfall on agricultural output "Locally Weighted Scatterplot Smoothing" (LOWESS) and linear spline fitted 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 Output and Irrigation

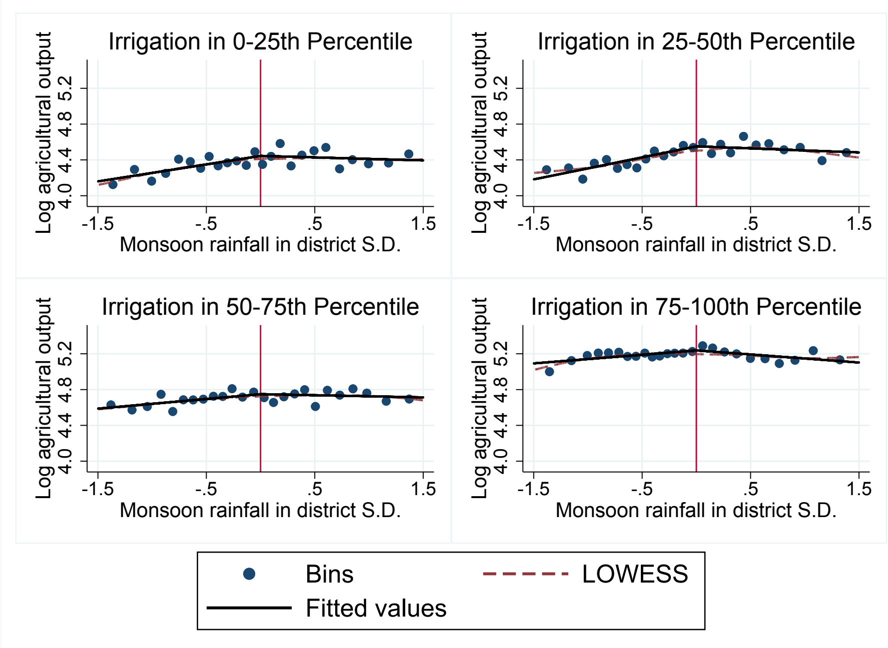


Figure 5: The figure presents binned scatterplots (25 bins per plot) for variations in monsoon rainfall and log agricultural output at different percentiles of irrigation. We also show Locally Weighted Scatterplot Smoothing (LOWESS) and linear spline fitted values.

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

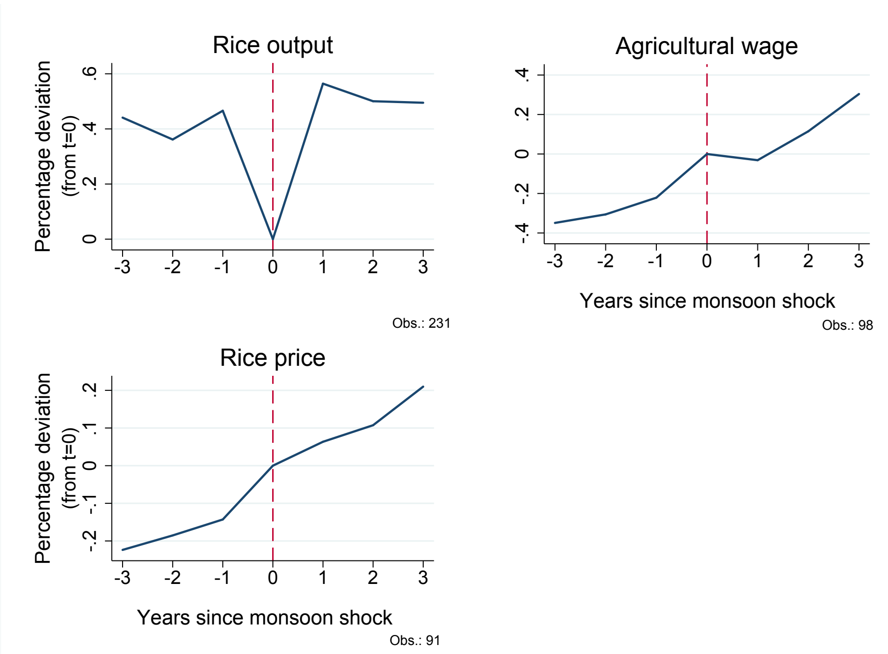


Figure 6: The graphs illustrate an event study for observed negative rainfall shocks of below -1.5 district standard deviation (SD), occurring at t=0, while in the remaining time period no single shock above/below 1 standard deviation has occurred. Only balanced data is used for plotting the graphs.

A.7 Response to Negative Local Rainfall Variation

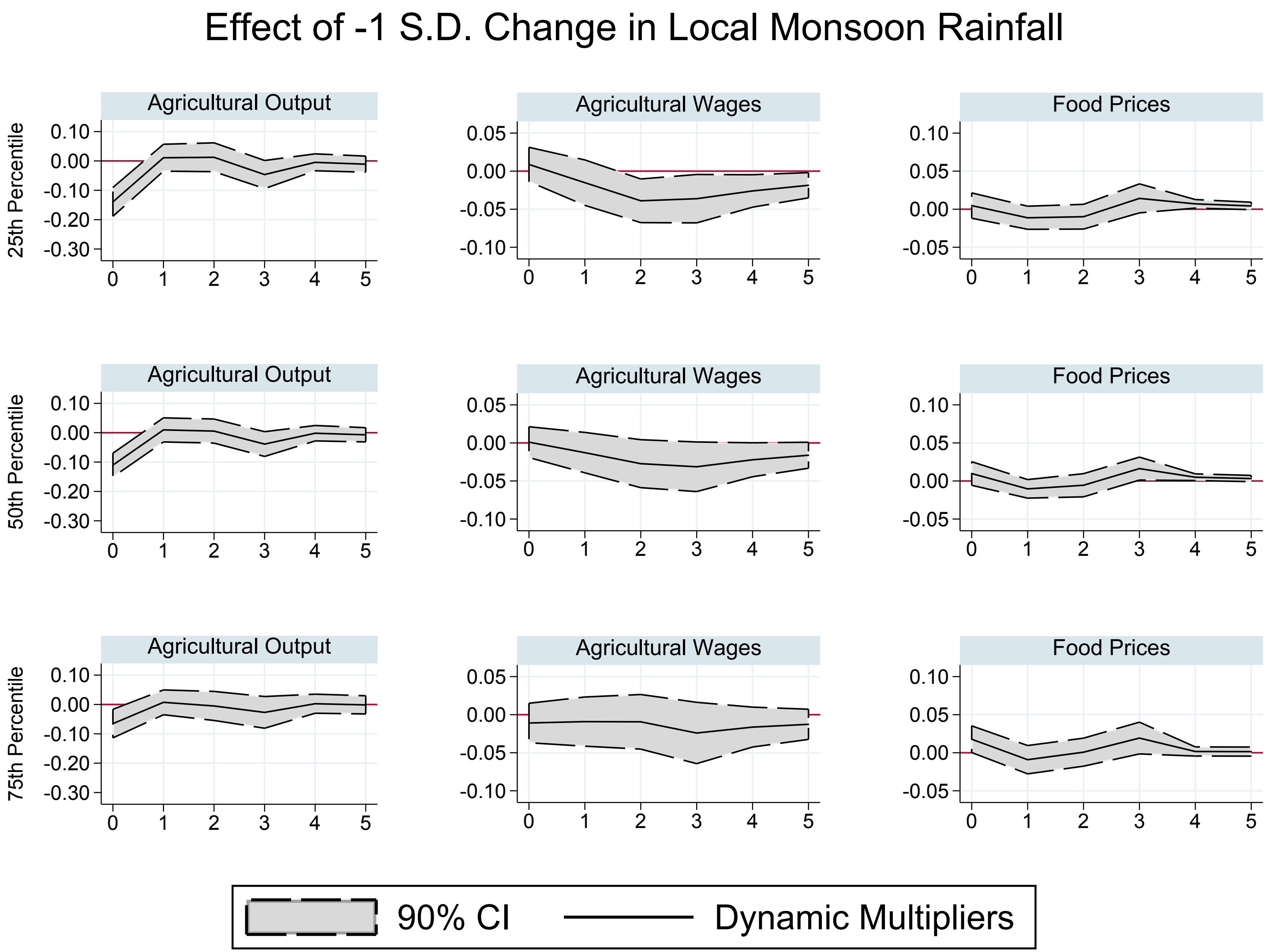


Figure 7: The figure illustrates the impulses in response to a positive purely local rainfall shock during the kharif season of one district standard deviation (SD). The black solid line is the point estimate. The gray area represents the 90% confidence interval over a 5 year time period. The effects 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

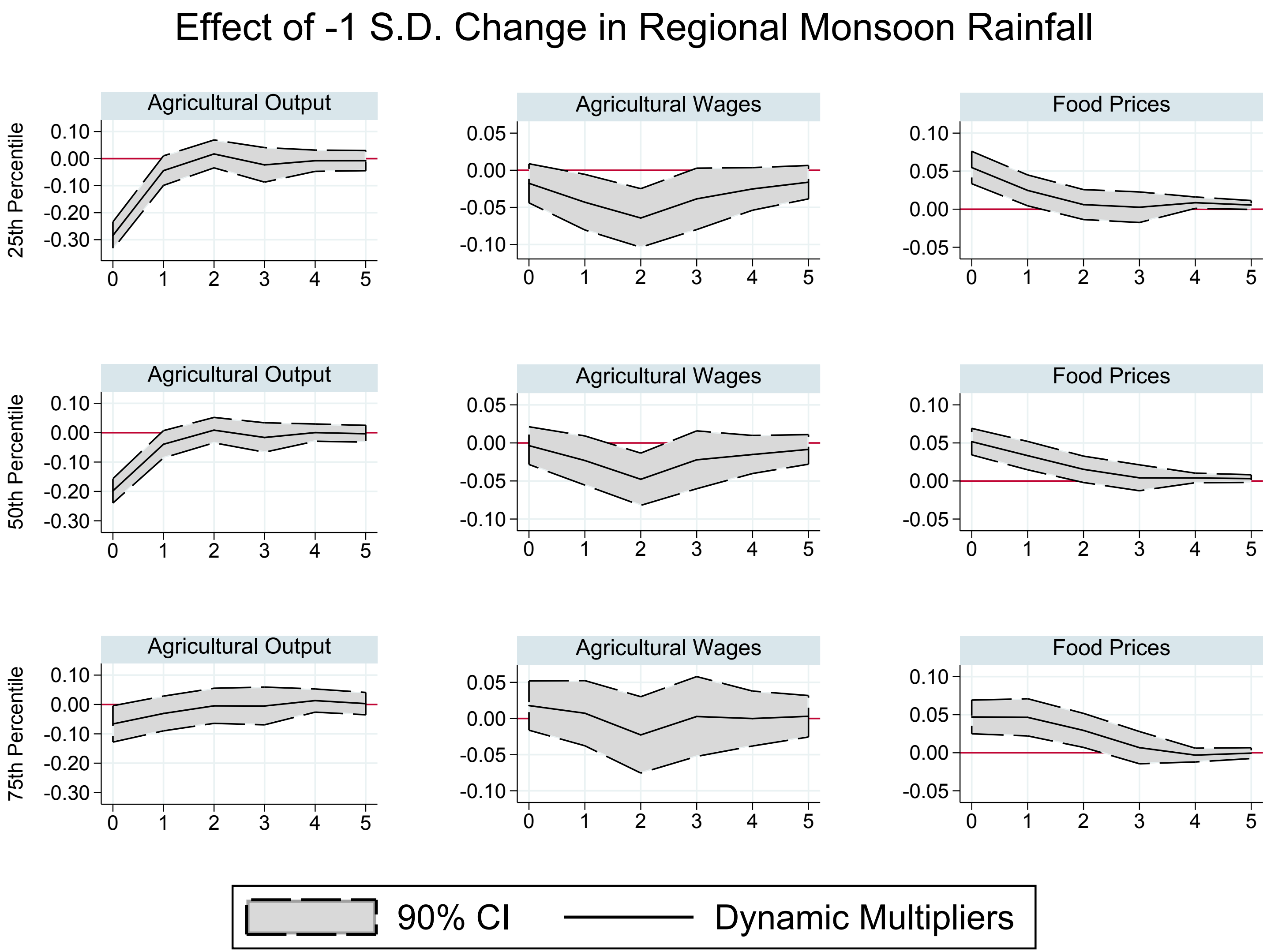


Figure 8: The figure illustrates the impulses in response to a negative regional rainfall shock during the kharif season of one district standard deviation (SD). The black solid line is the point estimate. The gray area represents the 90% confidence interval over a 5 year time period. The effects are 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

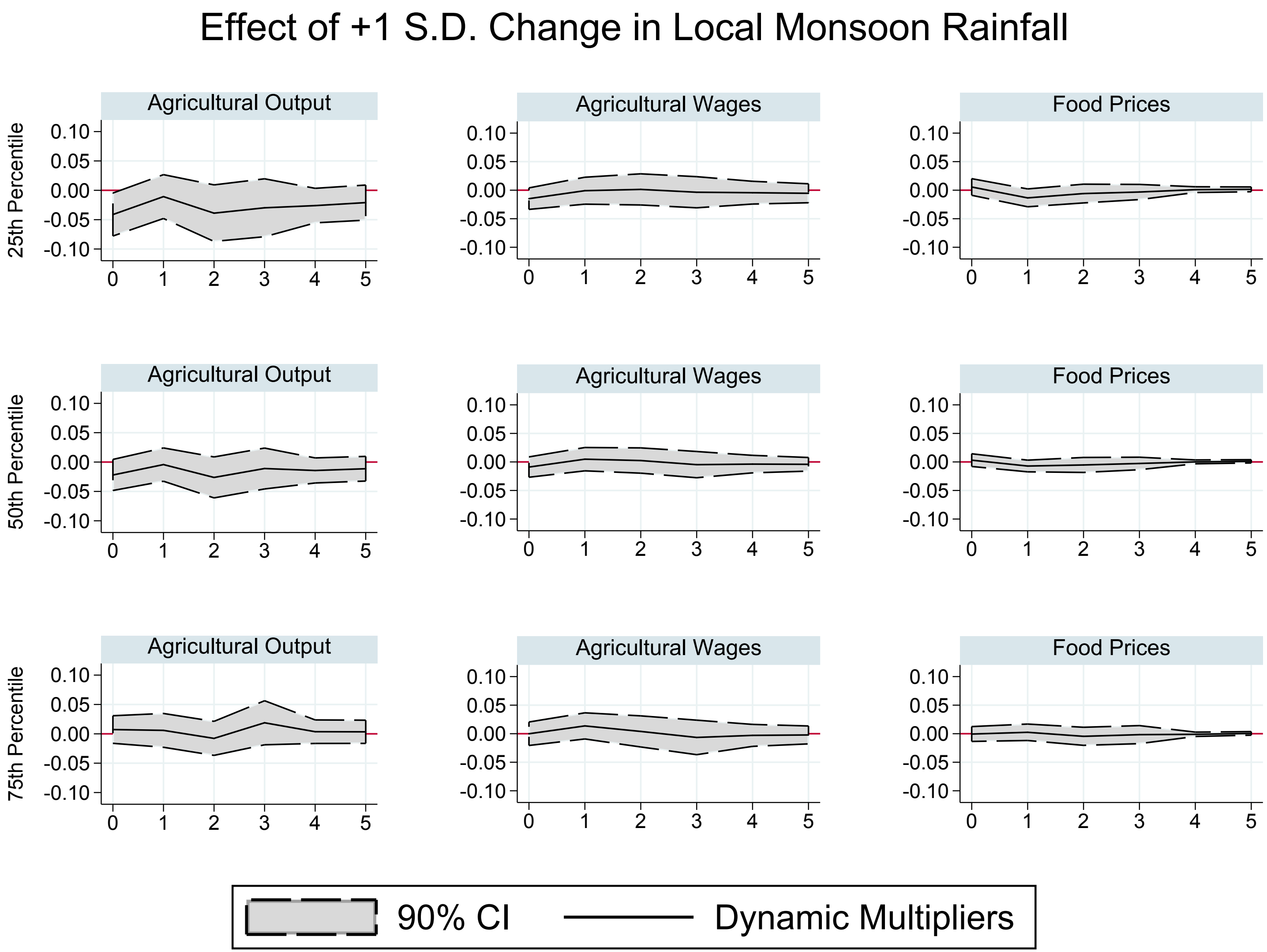


Figure 9: The figure illustrates the impulses in response to a positive purely local rainfall shock during the kharif season of one district standard deviation (SD). The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects 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

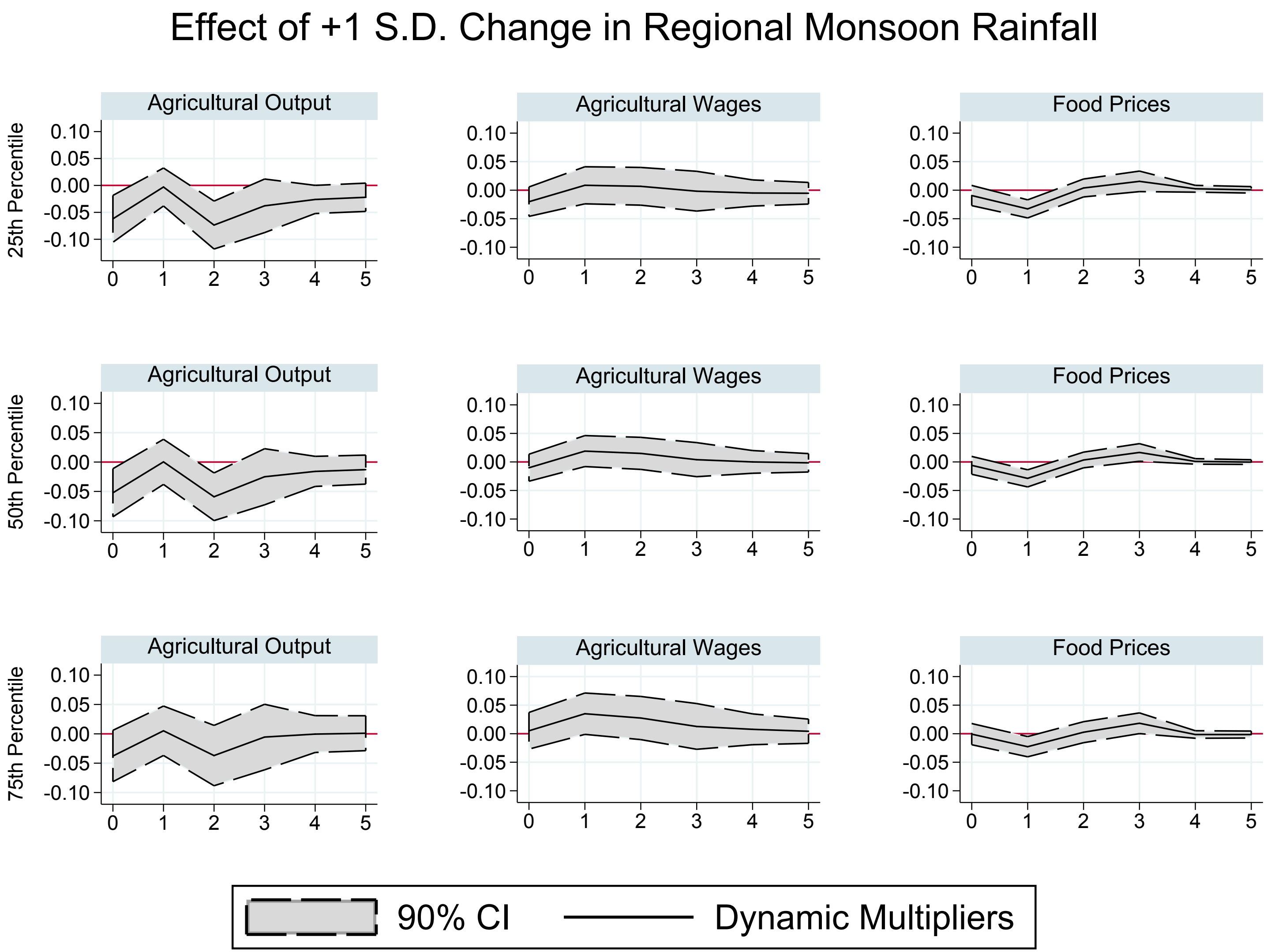


Figure 10: The figure illustrates the impulse in response to a positive regional rainfall shock during the kharif season of one district standard deviation (SD). The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects are 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

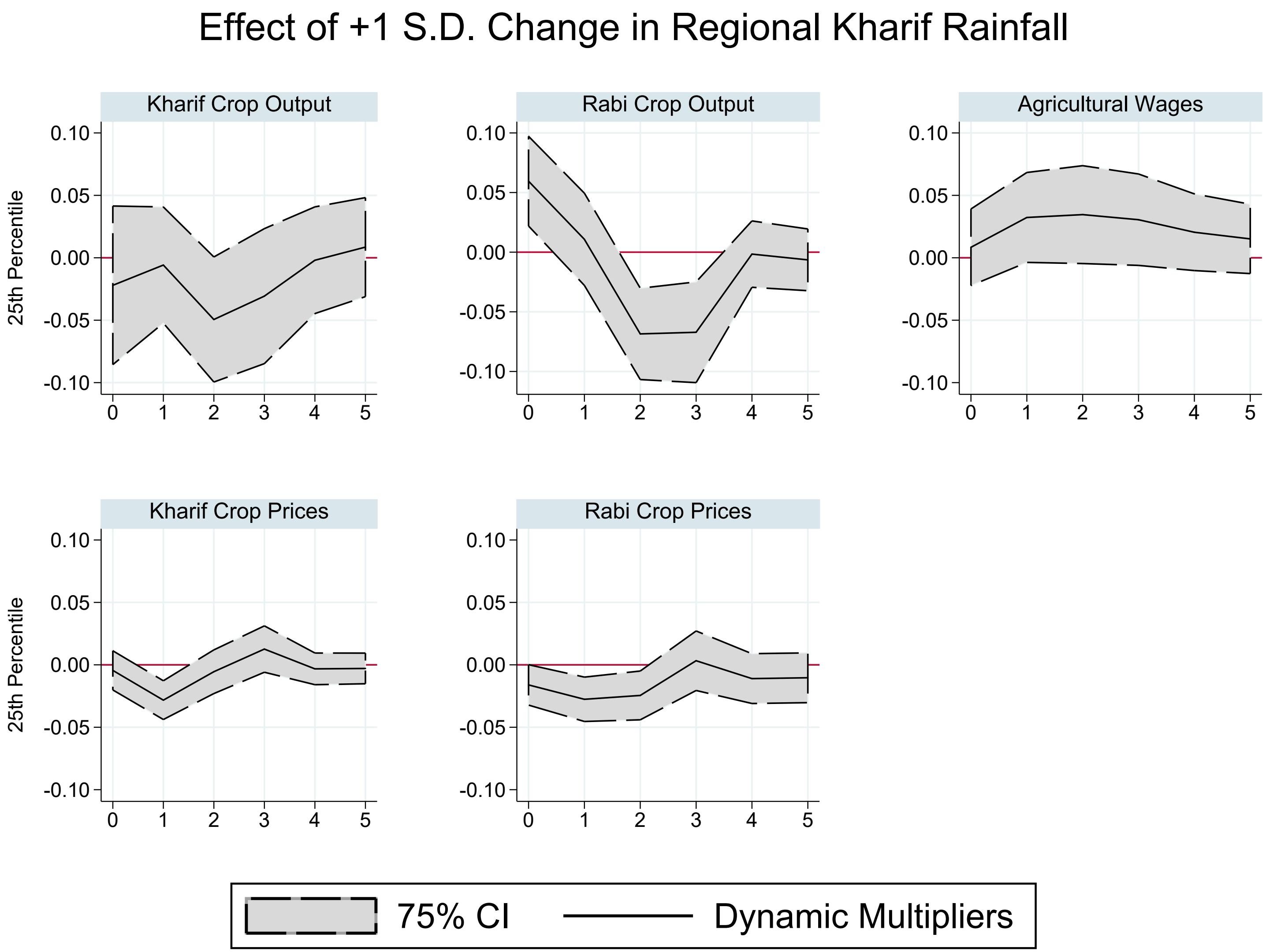


Figure 11: The figure illustrates the impulses in response to a positive regional rainfall shock during the kharif season of one district standard deviation (SD) on kharif crop output and prices, rabi crop output and prices, and agricultural wages. The number of observations at the selected lag-length is only 1277 due to a high number of missing values for rabi crop output and prices. For this reason, we adjust the confidence interval to be at the 75% level.

A.12 Response to Monsoon Temperature

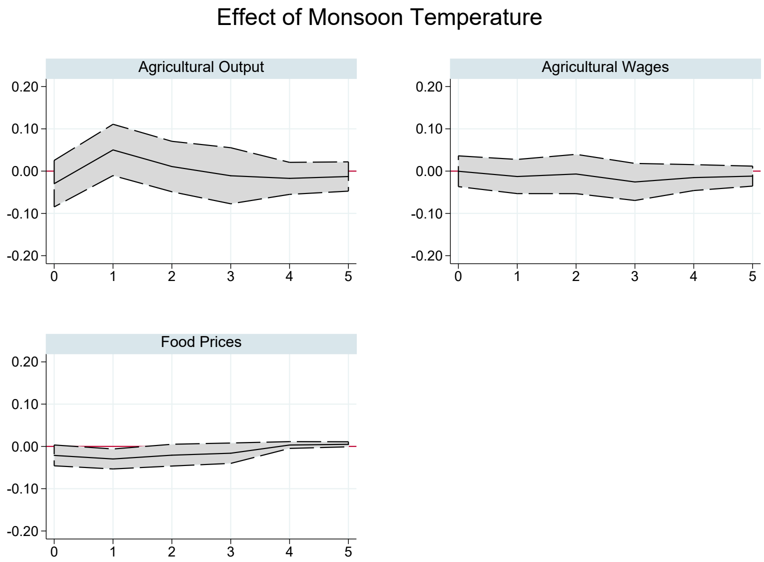


Figure 12: The figure illustrates the impulses in response to a monsoon season temperature shock of 1 degree above the district mean. The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The results are based on 2951 observations at the selected lag-length.

A.13 Response to Overall Rainfall Variation (pooled results across all levels of irrigation and all spatial dimensions)

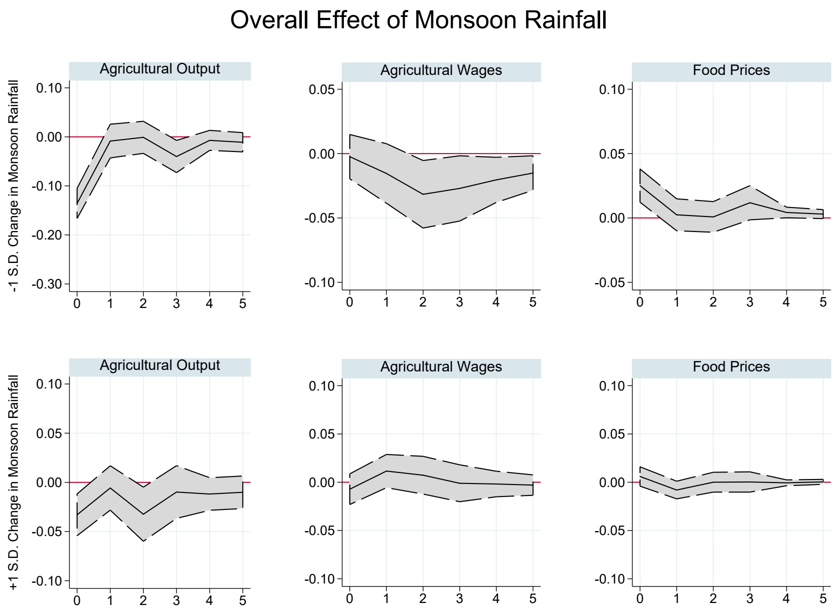


Figure 13: The figure illustrates the impulses in response to a negative (positive) shock in overall rainfall of one district SD. The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects are pooled across all levels of irrigation. The results are based on 2951 observations.

A.14 Pooled Results Across all Levels of Irrigation

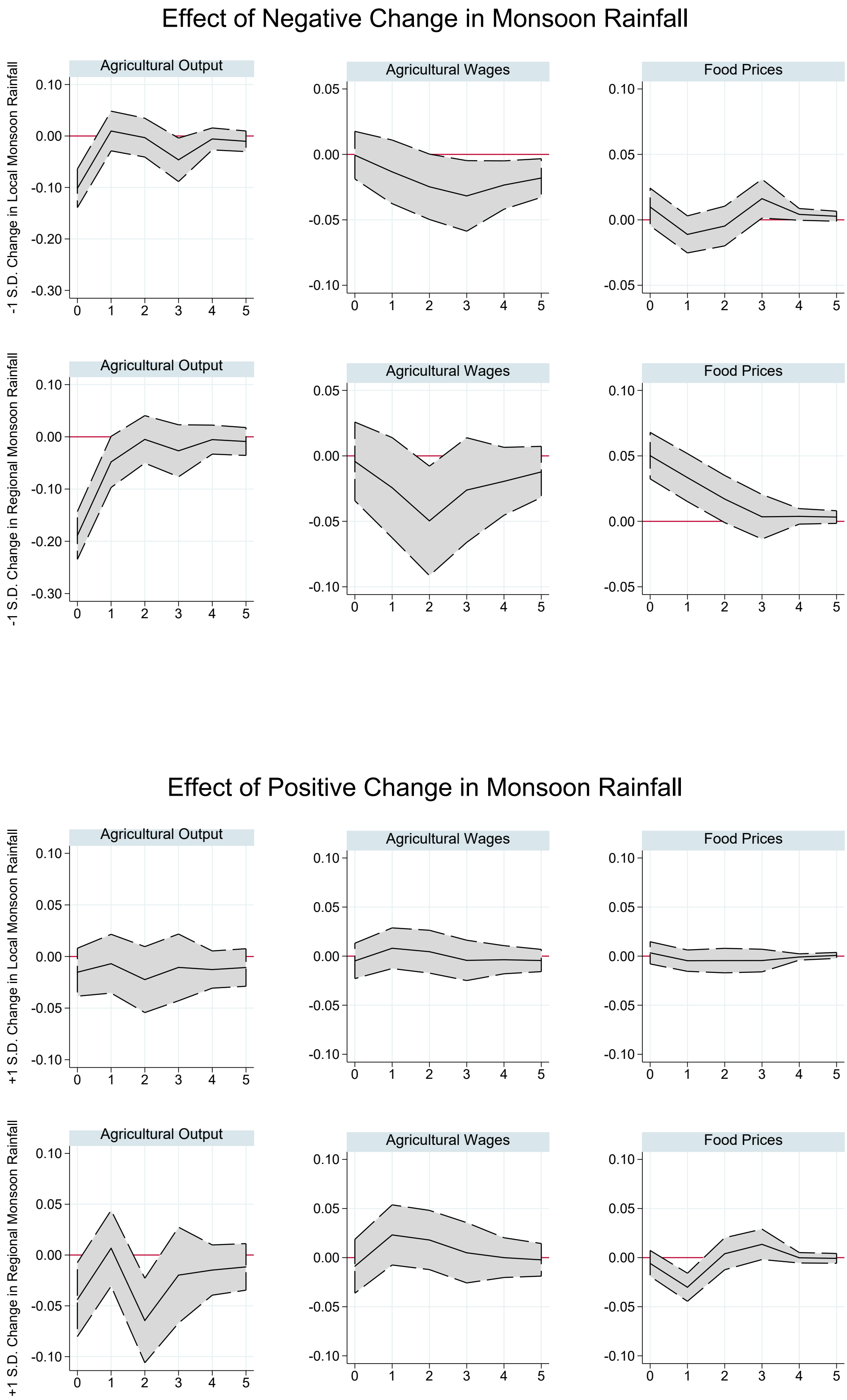


Figure 14: The figure illustrates the impulses in response to purely local and regional rainfall shocks during the kharif season of one district SD. The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects are pooled across all levels of irrigation. The results are based on 2951 observations.

A.15 Pooled Results Across all Spatial Dimensions

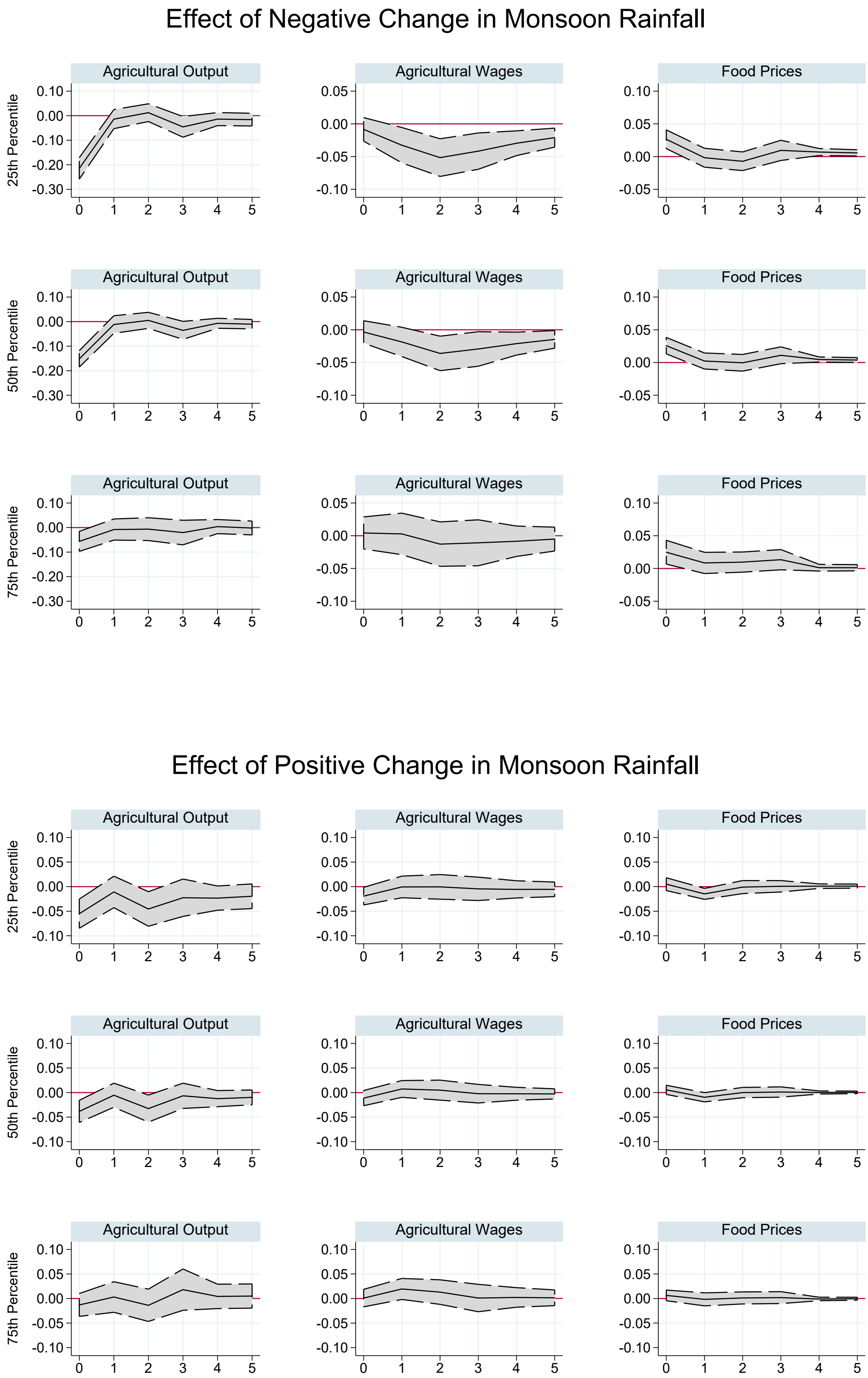


Figure 15: The figure illustrates the impulses in response to a negative (positive) shock in overall rainfall of one district SD. The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects are presented for different levels of irrigation. The results are based on 2951 observations.

A.16 Response to Overall Rainfall Variation (irrespective of the sign of the shock)

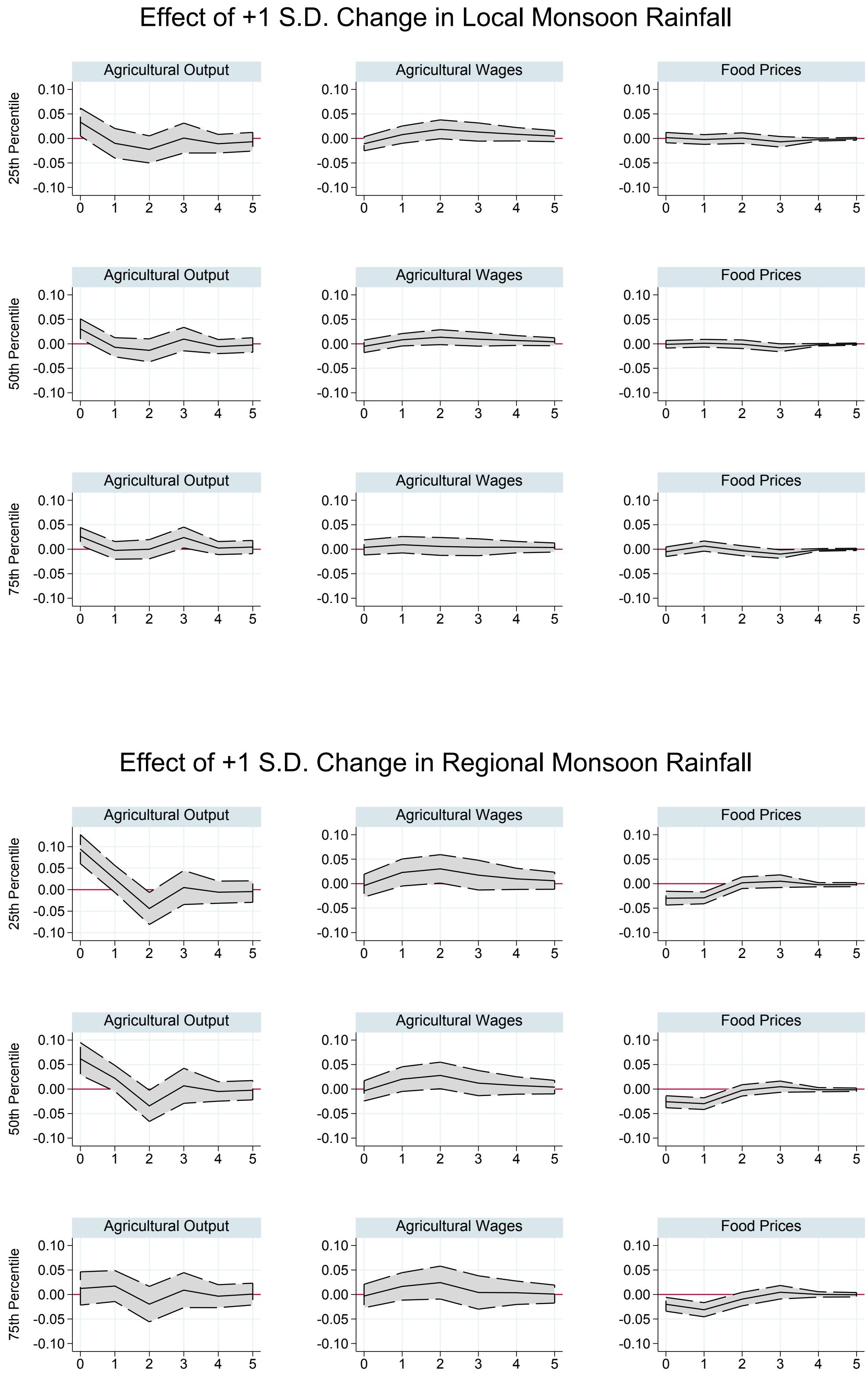


Figure 16: The figure illustrates the impulses to a purely local (regional) rainfall shock during the kharif season of one district SD. We do not distinguish between above and below normal rainfall. The black solid line is the point estimate. The grey area represents the 90% confidence interval over a 5 year time period. The effects are presented for different levels of irrigation. The results are based on 2951 observations.

A.17 Response to Negative Rainfall Shocks for 5-95% Sample

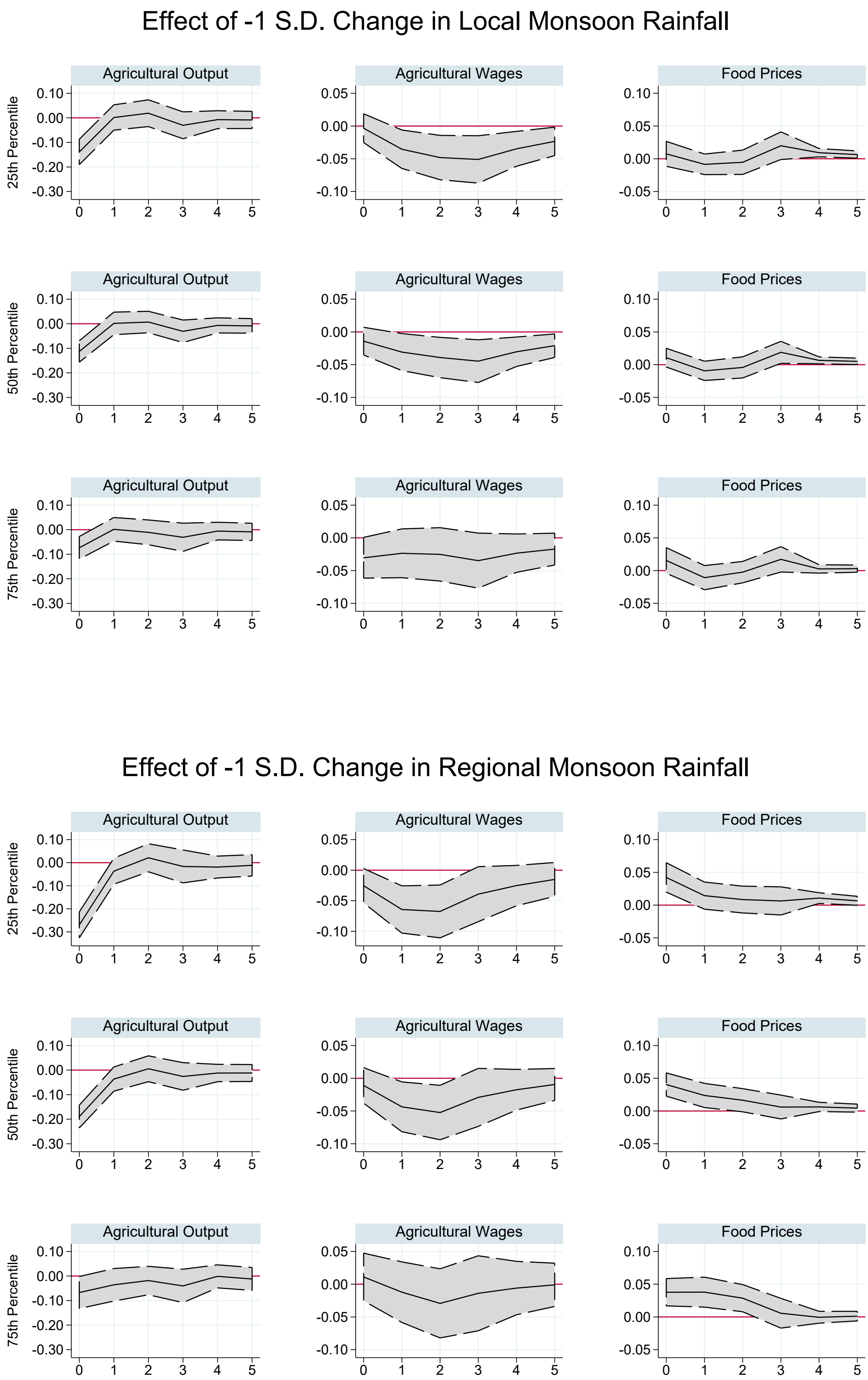
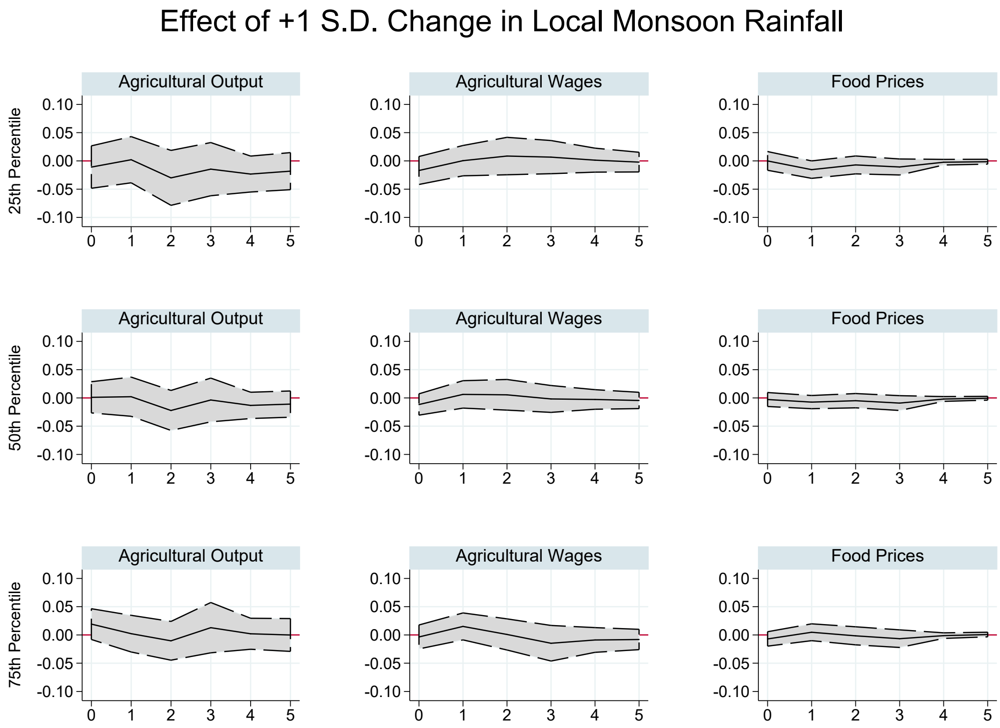


Figure 17: The figure illustrates the impulses in response to a negative purely local (regional) rainfall shock during the kharif season of one district SD for a sample that includes only districts within the 5th-95th percentile of rainfall variation in centimetres. The results are based on 2609 observations.

A.18 Response to Positive Rainfall Shocks for 5-95% Sample



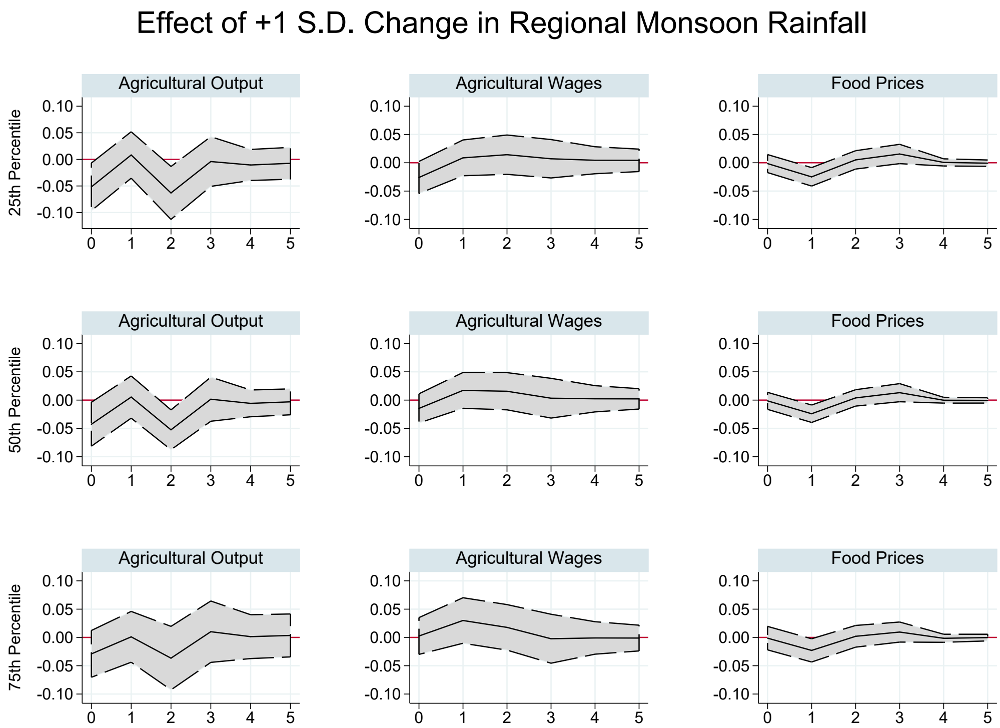


Figure 18: The figure illustrates the impulses in response to a positive purely local (regional) rainfall shock during the kharif season of one district SD for a sample that includes only districts within the 5th-95th percentile of rainfall variation in centimetres. The results are based on 2609 observations.

A.19 Response to Negative Rainfall Shocks for 1967-1991 Sample

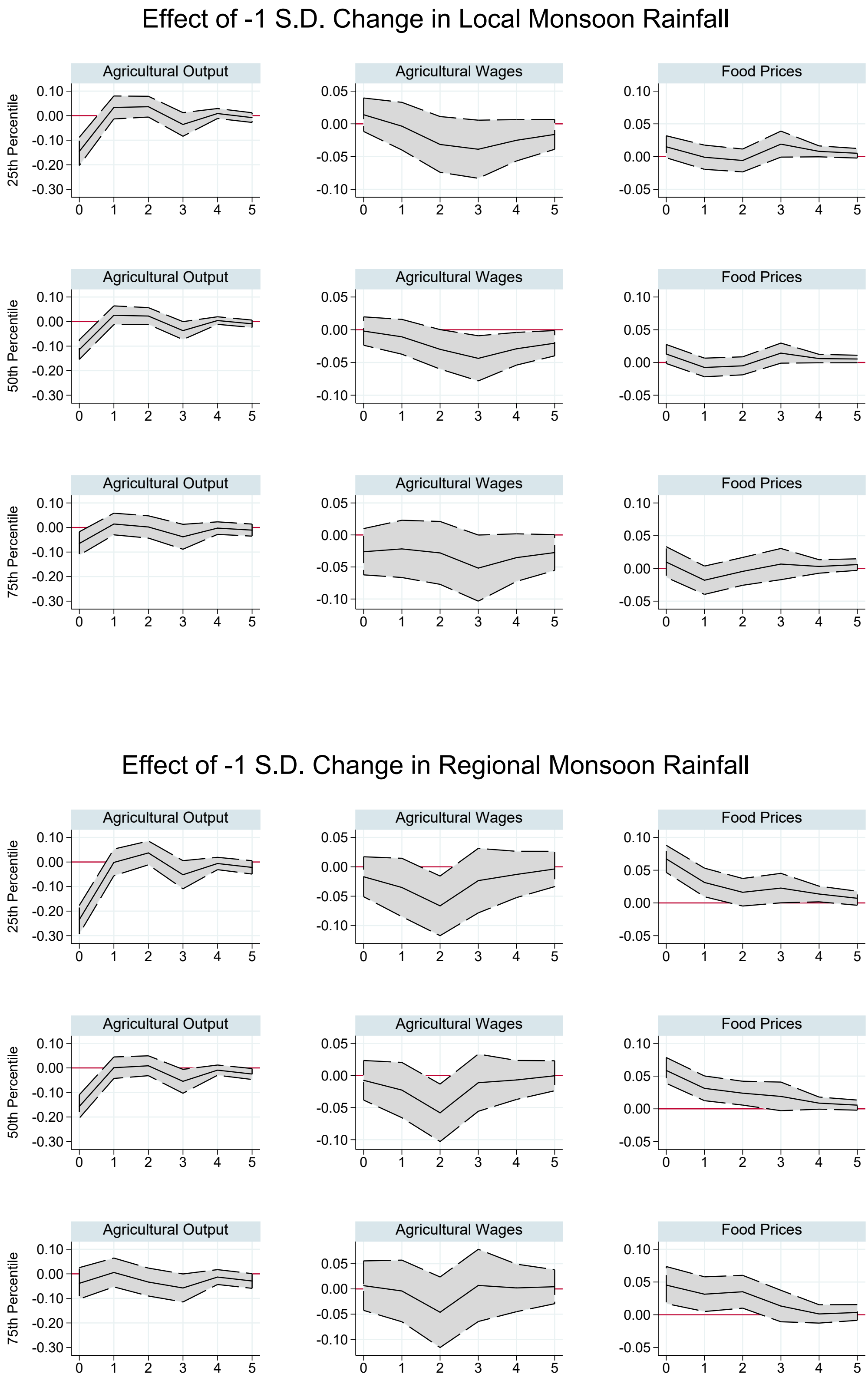


Figure 19: The figure illustrates the impulses in responses to a negative purely local (regional) rainfall shock during the kharif season of one district SD for a sample that includes only the years 1967-1991. The results are based on 2207 observations.

A.20 Response to Positive Rainfall Shocks for 1967-1991 Sample

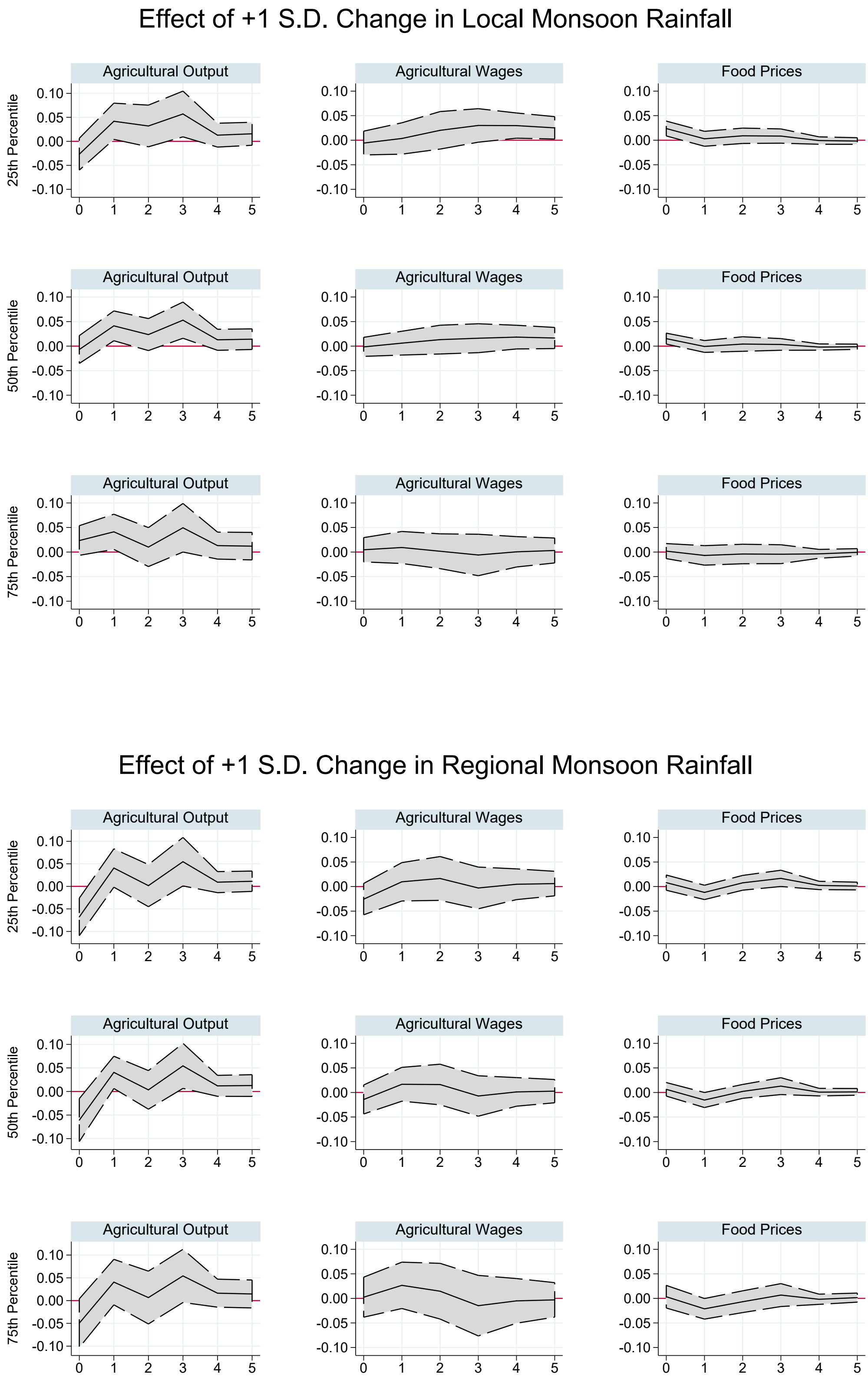


Figure 20: The figure illustrates the impulses in responses to a positive purely local (regional) rainfall shock during the kharif season of one district SD for a sample that includes only the years 1967-1991. The results are based on 2207 observations.

A.21 Response to Negative Rainfall Shocks for 1981-2005 Sample

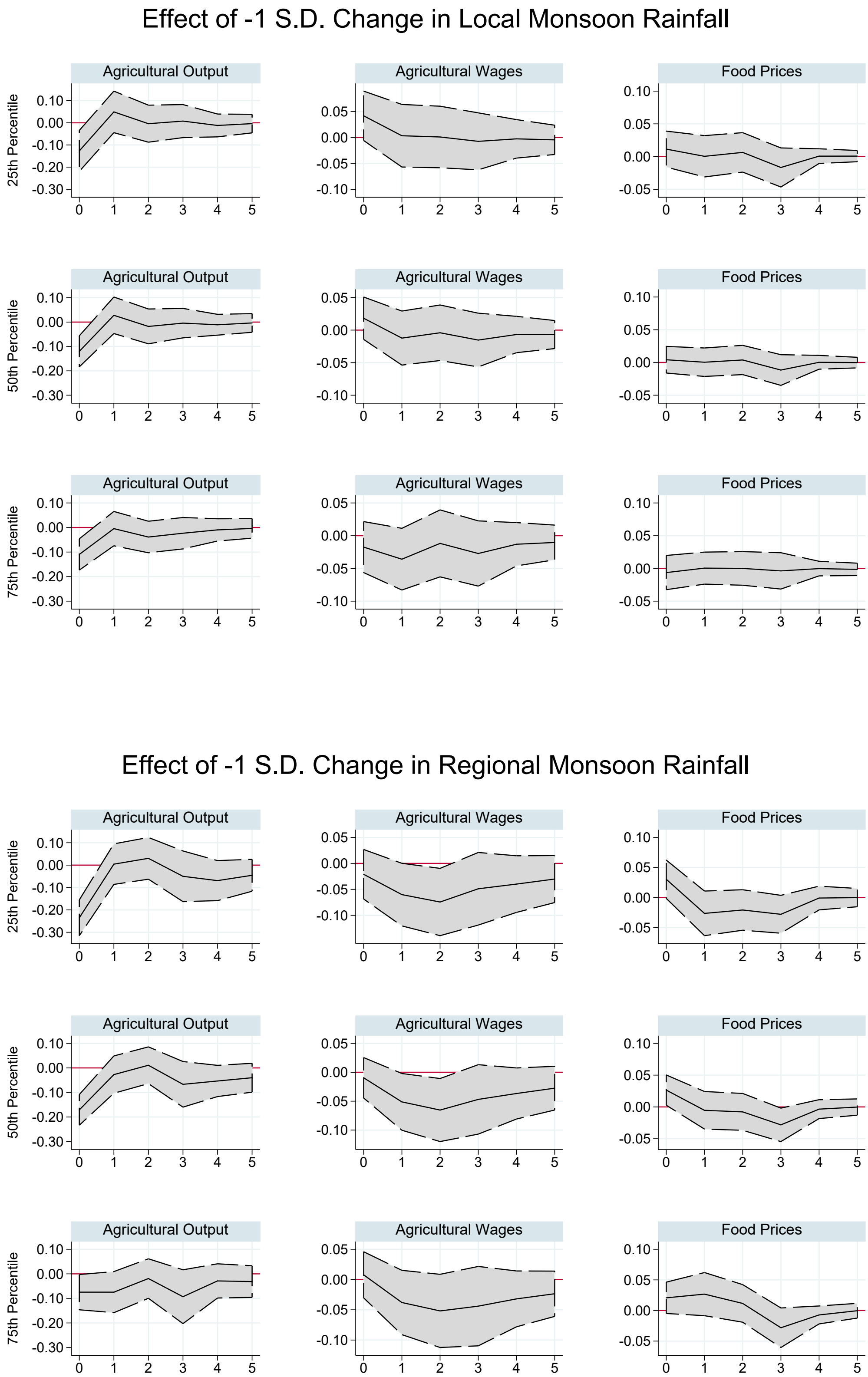


Figure 21: The figure illustrates the impulses in response to a negative purely local (regional) rainfall shock during the kharif season of one district SD for a sample that includes only the years 1981-2005. The results are based on 1413 observations.

A.22 Response to Positive Rainfall Shocks for 1981-2005 Sample

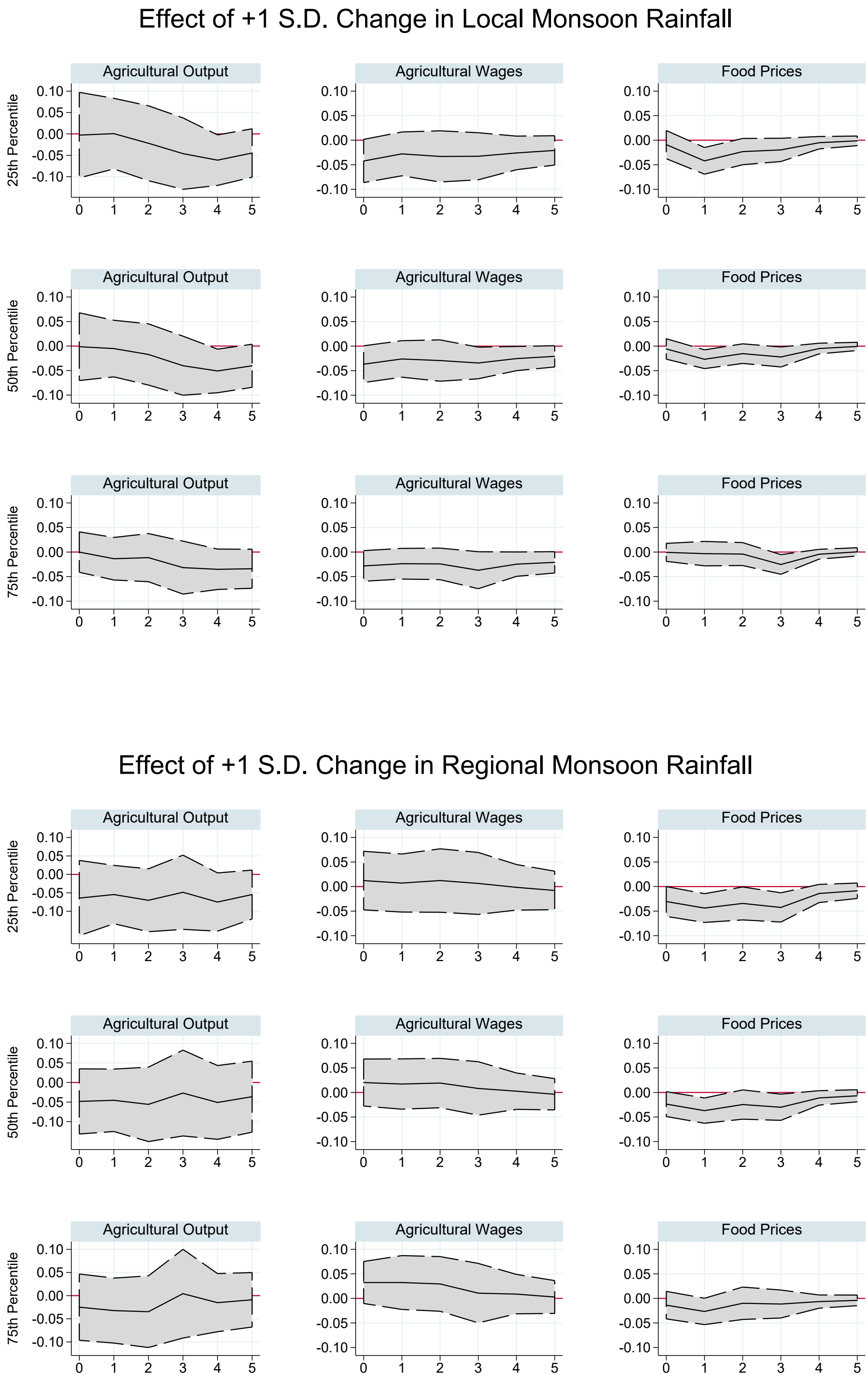
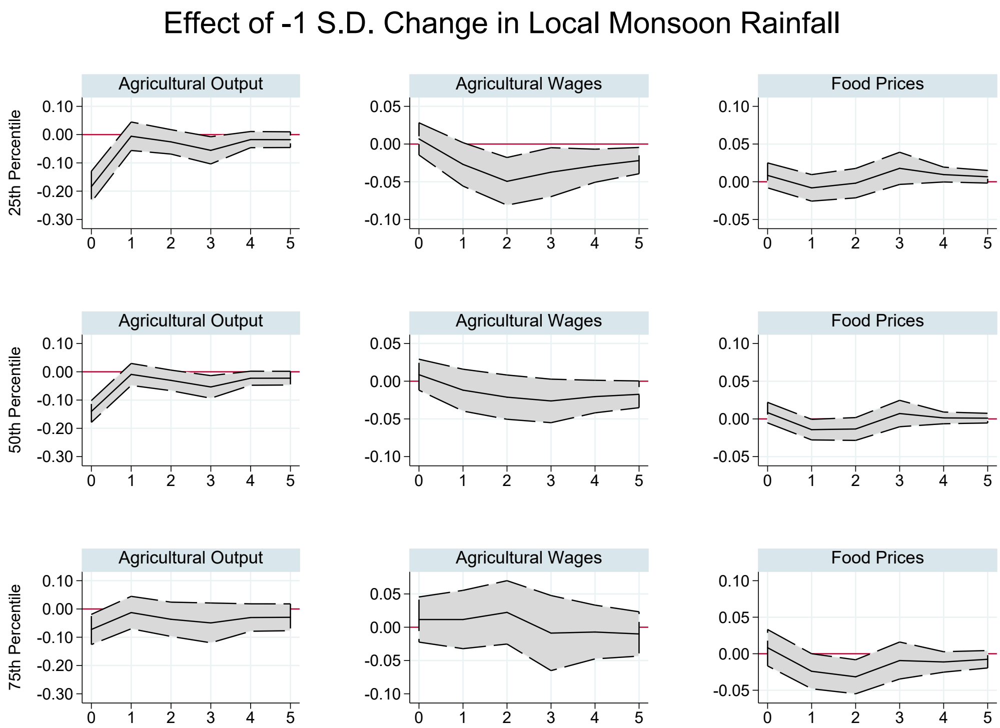


Figure 22: The figure illustrates the impulses in response to a positive purely local (regional) rainfall shock during the kharif season of one district SD for a sample that includes only the years 1981-2005. The results are based on 1413 observations.

A.23 Response to Negative Rainfall Shocks for Southern & Eastern States



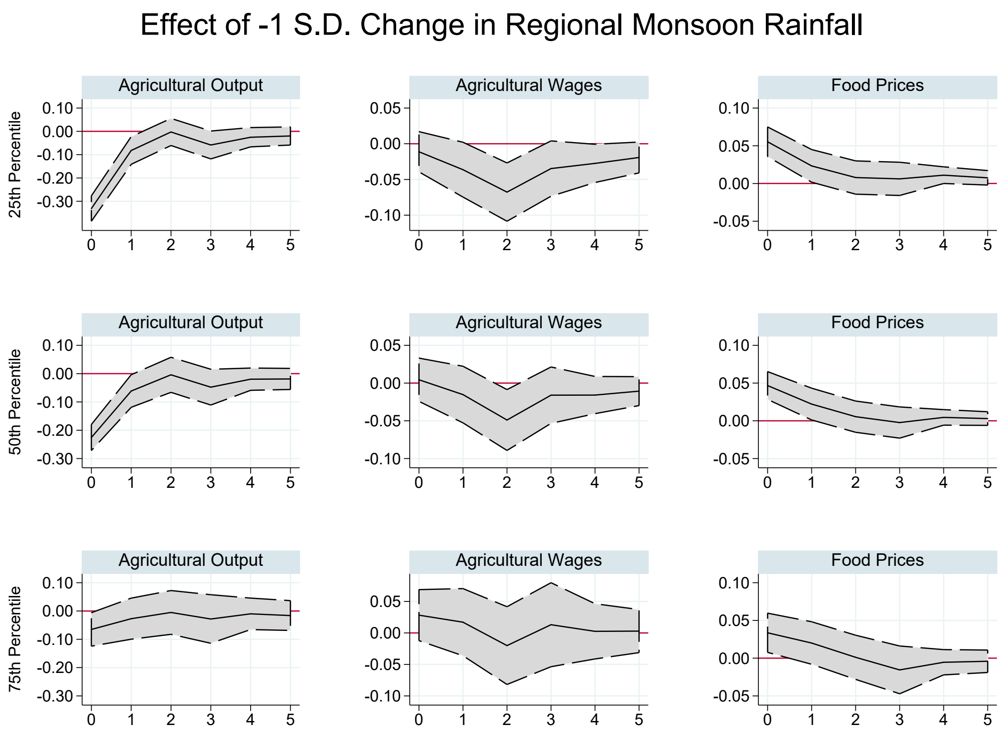
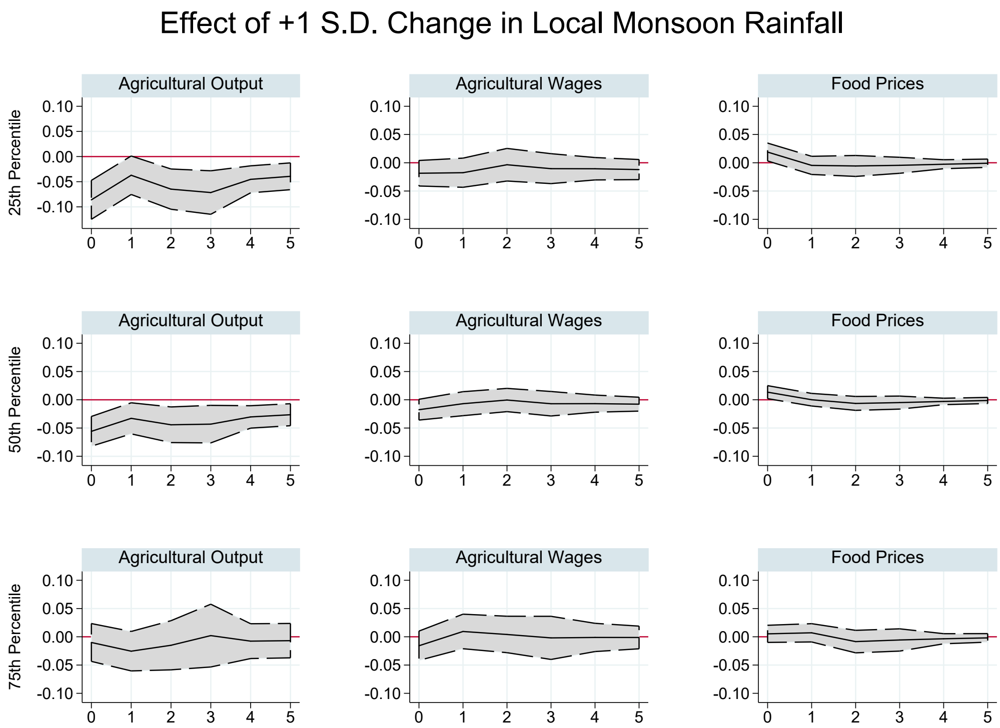


Figure 23: The figure illustrates the impulses in response to a negative purely local (regional) rainfall shock during the kharif season of one district SD for a sample that includes only states in the south and east of India, where monsoon rainfall arrives usually before the 10-15th of June. The results are based on 2257 observations.

A.24 Response to Positive Rainfall Shocks for Southern & Eastern States



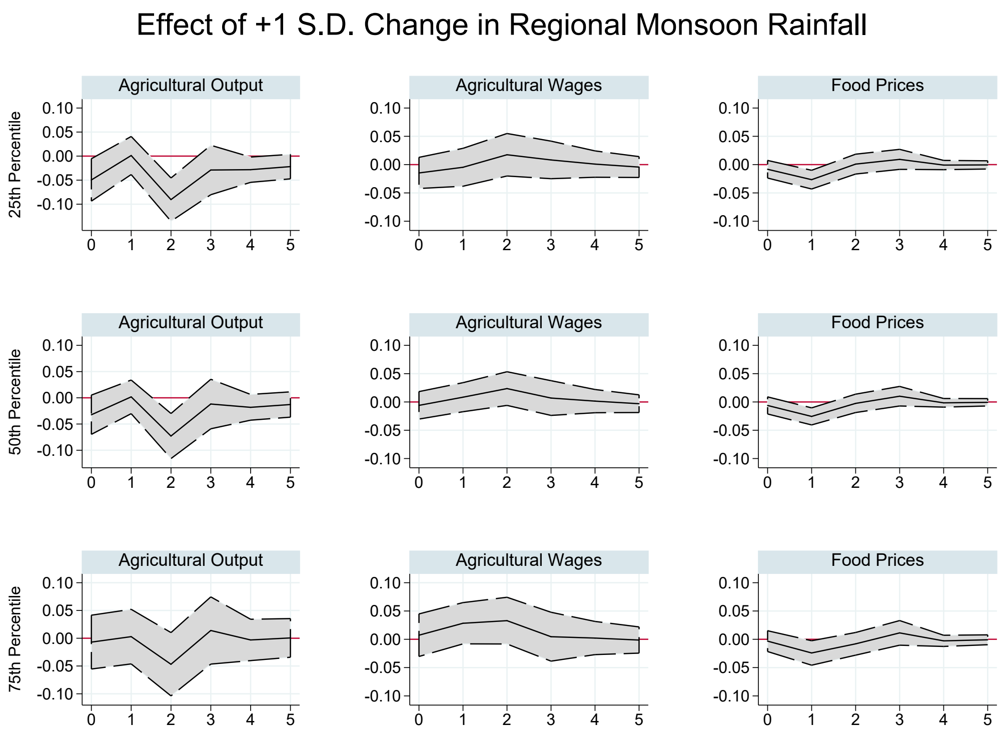


Figure 24: The figure illustrates the impulses in response to a positive purely local (regional) rainfall shock during the kharif season of one district SD for a sample that includes only states in the south and east of India, where monsoon rainfall arrives usually before the 10-15th of June. The results are based on 2257 observations.

A.25 Response to Negative Rainfall Shocks for Northern & Western States

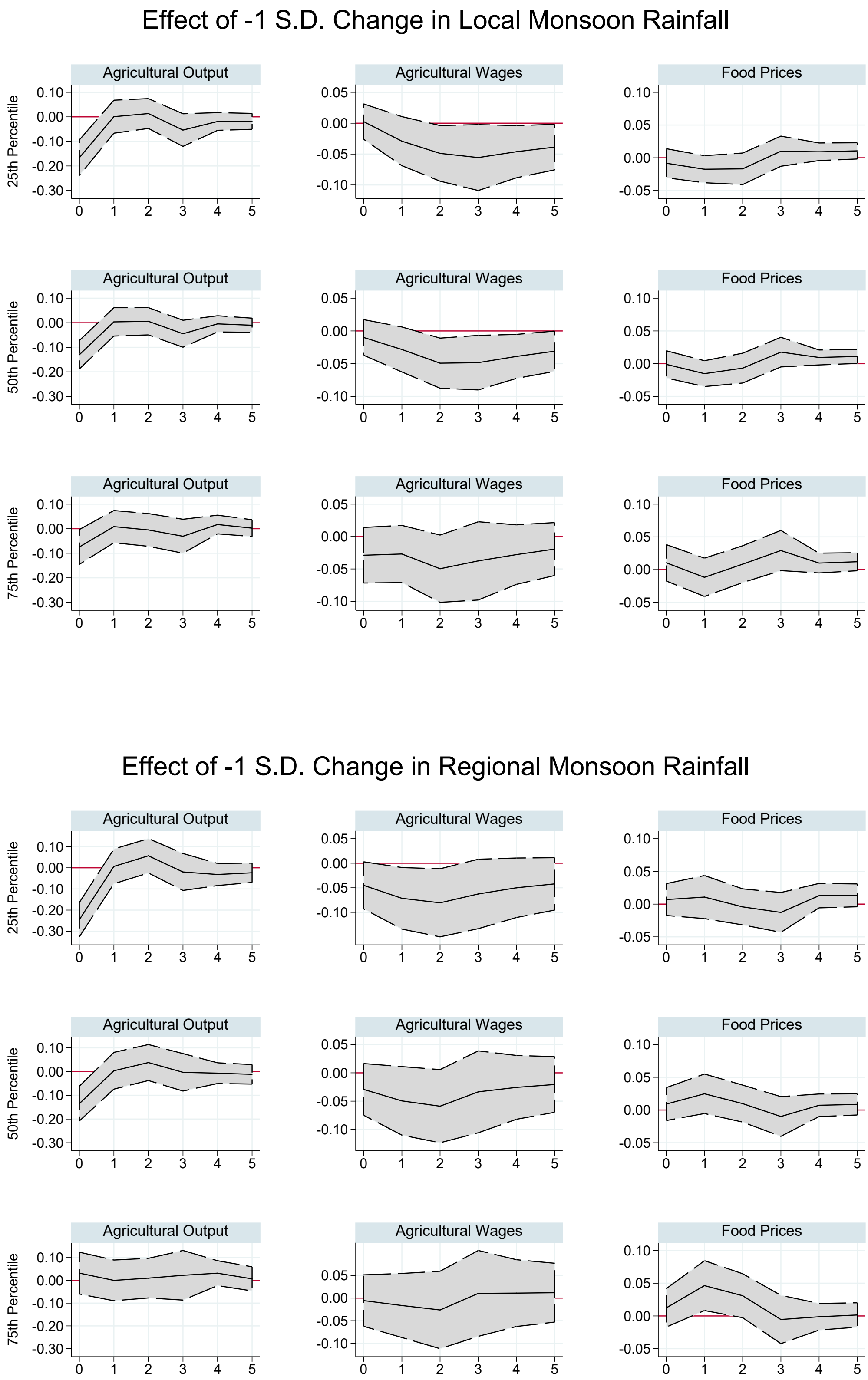
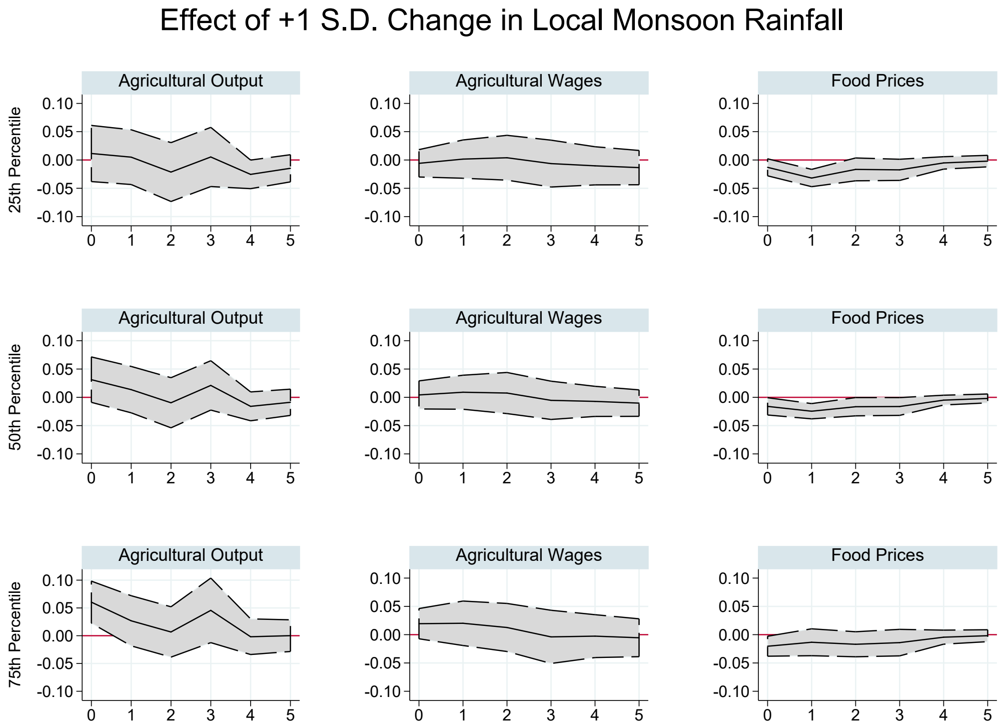


Figure 25: The figure illustrates the impulses in response to a negative purely local (regional) rainfall shock during the kharif season of one district SD for a sample that includes only states in the north and west of India, where monsoon rainfall arrives usually after the 10-15th of June. The results are based on 1766 observations.

A.26 Response to Positive Rainfall Shocks for Northern & Western States



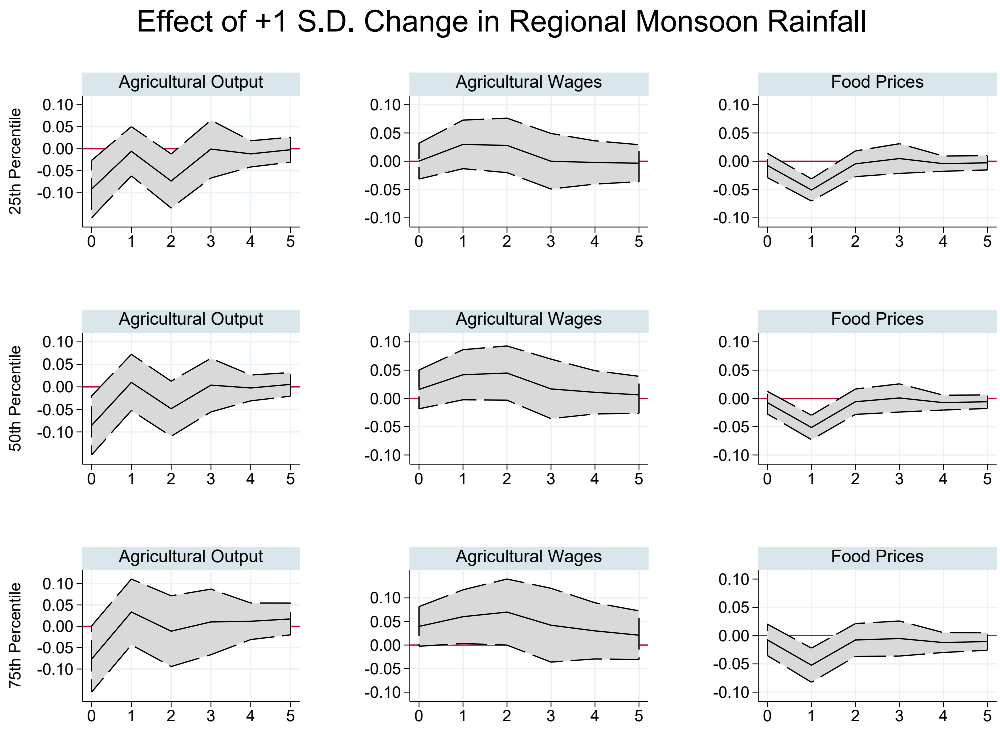


Figure 26: The figure illustrates the impulses in response to a positive purely local (regional) rainfall shock during the kharif season of one district SD for a sample that includes only states in the north and west of India, where monsoon rainfall arrives usually after the 10-15th of June. The results are based on 1766 observations.

B Tables

B.1 Summary Statistics

	Mean	Standard Deviation	Observations
Rainfall Variables:			
Annual Rainfall (in cm)	116.62	67.00	12,087
Monsoon Rainfall (in cm)	98.08	56.66	12,087
Monsoon Season Rainfall SD.	0.00	1.00	12,087
Local Monsoon Rainfall SD.	0.00	0.59	12,087
Aggregate Monsoon Rainfall SD.	0.00	0.79	12,087
Agricultural Sector Variables:			
Log agricultural output (ton/km^2)	4.69	0.69	10,641
Log agricultural wage ($Rupee$)	2.44	1.15	8,877
Log price index ($Rupee/ton$)	7.66	0.78	8,525
Other Variables:			
Share of irrigated land	0.33	0.25	11,068
Monsoon temperature (demeaned)	0.00	0.46	12,087

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

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 & 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 rastered rainfall and air temperature data from Willmott & Matsuura (2012) is available on a monthly basis from 1900-2010 with a resolution of $0.5° \times 0.5°$. We interpolate this raster dataset to a $0.1° \times 0.1°$ raster, 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-Oktober).

C.2 Agricultural Output

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 labor 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 output into an overall rice output 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.