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The Persistent Effects of Monsoon Rainfall Shocks in India: A Nonlinear VAR Approach*

Björn Brey† Matthias S. Hertweck‡

University of Nottingham University of Konstanz

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Abstract

This paper examines the effects of monsoon rainfall shocks on output, wages, and prices in the Indian agricultural sector. First, we find that the effects are highly asymmetric. If monsoon rainfall falls one standard deviation below the district mean, agricultural output falls on average by -16% — whereas a positive shock has no significant effects. Second, the drop in agricultural output is very short-lived, but it elicits a persistent decline (increase) in wages (food prices). This indicates that famines are mainly caused by a persistent disruption of the food acquisition process, rather than by a shortage in food supply.

JEL Classifications: C22, E32, O13, Q11
Keywords: rainfall shocks, agricultural output, wages, food prices

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†Contact Address: University of Nottingham, School of Economics, Sir Clive Granger Building, University Park, Nottingham NG72RD. Email: lexbb8@nottingham.ac.uk

‡Contact Address: University of Konstanz, Department of Economics, Box 145, 78457 Konstanz, Germany. Email: matthias.hertweck@uni-konstanz.de, Homepage: http://www.hertweck.org/

1 Introduction

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).[1] 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 live in precarious conditions and are particularly vulnerable to income and employment uncertainty (see e.g. Fan et al. 1998; Himanshu 2007; Asian Development Bank 2011).[2] One important source of fluctuations in the Indian agricultural sector are changes 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.[3]

For this purpose, we estimate a non-linear panel VAR based on data from 314 Indian districts from 1966-2011. Our main result is that the effects of monsoon rainfall shocks are highly asymmetric. If monsoon rainfall falls one standard deviation below the district mean, agricultural output falls on average by -16% — whereas positive shocks have no significant effects. The drop in agricultural output is very short-lived, but it elicits a persistent decline (increase) in wages (food prices). In particular, we note that wages in the Indian agricultural sector respond much more sensitively to shortfalls in output than in industrialized countries (Rosenzweig & Binswanger 1992, Freeman & Oostendorp 2002)[4]. The pattern of falling wages and rising food prices has important distributional effects, as it favors landowners over the rural poor.

Our paper thus allows to address the hypothesis of Sen (1981). Accordingly, famines are not only due to the (direct) shortfall in agricultural output, but rather by the breakdown of the food acquisition process. The combination of lower wages and higher food prices for a protracted period of time is particularly harmful to the rural poor (since higher food prices do not translate into higher wages of agricultural workers, see Lanjouw & Shariff 2004 and De Janvry & Sadoulet 2009). Given incomplete credit markets (Dercon 2002), droughts thus lead to increased (temporary) migration movements to urban areas and, hence, to substantial spillover effects to the Indian non-agricultural sector (a phenomenon not common in developed economies).[5] Additionally, as years with abundant rain do not lead to increases in the agricultural wage, the predicted increase in the variation of monsoon rainfall (see Challinor et al. 2006 and Christensen et al. 2007), will likely have a severe impact on the livelihoods of the poor in India.

[1] The agricultural sector accounts for about 17% of the Indian GDP (World Bank 2016).

[2] These numbers provided by the Indian government should however be seen as a lower-bound to poverty as they systematically underestimate poverty compared to international measures of poverty and measures in other Asian countries (Sivakumar & Sarvalingam 2010).

[3] The obtained findings could also be transferred to other developing economies where agriculture is predominantly rain-fed (particularly, in South East Asia).

[4] The income variation in rural India is likely to rise even further since monsoon rainfall is predicted to become more variable in the future (Challinor et al. 2006; Christensen et al. 2007).

[5] There is nearly no geographical migration between rural areas in India with only about 10% of (temporary) migrants taking up a agricultural occupation when migrating (see Mosse et al. 2002; Topalova 2010).

Among the previous literature that has attempted to quantify the consequences of productivity variations in agriculture on the livelihoods of the poor (see e.g. Mooley & Parthasarathy 1982, Adams 1989, Paxson 1992, Rosenzweig & Wolpin 1993), our paper is most closely related to Jayachandran (2006). In contrast to her static framework, we estimate a VAR model which is able to capture the persistent movements in output, wages and food prices after monsoon rainfall shocks. Moreover, consistent with the crop science literature (Steduto et al. 2012), we allow for asymmetric effects of positive vs. negative monsoon rainfall shocks. This explains why we find that agricultural output falls by -16.1% (rises insignificantly by 0.7%) when monsoon rainfall falls (rises) one standard deviation below (above) the district mean — whereas Jayachandran's (2006) symmetric estimate is equal to 5.4%. To our knowledge, the only other empirical study that has tried to account for non-linear effect of rainfall in India is the one by Gadgil & Gadgil (2006). In their study, however, the non-linear effect of rainfall on agricultural output nearly exclusively arises in cases of extreme rainfall variations (attributed to the effect of floods). Gadgil & Gadgil (2006) use a quadratic term to capture the non-linearity. In contrast, our results highlight that the non-linear effect of rainfall is not just occurring at the extremes, but that in general rainfall above the average-level has only a minimal effect on agricultural output — which is in strong contrast to the effect of less than usual rainfall. Further, our study profits from the use of district-level data, which improves results through exploiting the within variation in comparison to the time-series data used by Gadgil & Gadgil (2006).

The remainder of this paper is structured as follows: Section 2 presents the data on variations in rainfall and the agricultural sector, Section 3 outlines the empirical methodology and Section 4 discusses the results and sensitivity of the panel VAR estimates. Finally, Section 5 concludes.

2 Data

This Section outlines the data used. Subsection 2.1 presents the data sources and how the used variables are constructed, while Subsection 2.2 presents the patterns observed in the data in more detail.

2.1 Data Sources

The panel dataset we use builds to a vast extend on the data in the ICRISAT-dataset providing comparable data on rainfall, prices of agricultural products, quantity produced, and the area under cultivation, agricultural wages and irrigation across 314 Indian districts (data has been appropriated to 1966 district-boundaries) for a time-period covering 1966 to 2011. From this dataset we drop all 20 districts that changed states when Chhattisgarh, Jharkhand and Uttarakhand were formed in 2000. Following Jayachandran (2006) we exclude all 14 districts with a measured altitude above 600 meters since the relationship between rainfall and crop

yield appears to weaken with increased elevation.[6] We extend this dataset by adding data on the Indian GDP deflator obtained from IndexMundi and adjust agricultural prices and wages to be in real terms. This is especially important for capturing the adjustment of wages due to nominal wage rigidities (Kaur 2014).

For creating the data on agricultural output we use the quantity produced and area under cultivation for rice, wheat and sugar cane.[7] Agricultural output is defined as the amount produced per $1000m^2$ for the three crops taken in logarithm and weighted by the area of cultivation:

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

with i denoting the crop-type, t the year and n the district. Analogously we weight the different crop prices to create a measure for the price of food in a district: [8]

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

As outlined in Section 1, agriculture in India is predominantly rain fed and the monsoon, from June to August, is the main growing season (Coffey et al. 2015). This is particularly pronounced for rice where 90% of the harvest is produced in that time period (Dorosh 2001). We standardize monsoon rainfall by districts through subtracting the mean monsoon rainfall (in mm) over the sample period from yearly monsoon rainfall in the respective district and divide it by the district's standard deviation of monsoon rainfall:

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

The reason for standardizing the changes in monsoon rainfall by district is twofold: (i) farmers in districts with low monsoon rainfall will plant crops that require in general lower amounts of water and vice versa and (ii) farmers in districts with high rainfall variation will due to risk-aversion plant crop strains and use technologies that reduce the sensitivity of yield to rainfall variations even-tough this reduces expected profits (Rosenzweig & Binswanger 1992). As with

[6] In addition to those changes we exclude all observations before 1966 due to a considerable number of outliers, correct errors of magnitude 10 in the price data before 1970 for 11 districts, and drop all observations for prices and wages that are reported as zero.

[7] We opt against using bajra, jowar, maize, rice and wheat as done by Jayachandran (2006) due to a substantial amount of missing values for bajra, jowar and maize. Further, it appears that rice (1), wheat (4) and sugar cane (5) have been the three most important agricultural products as depicted by FAOSTAT data in terms of total value (ranking in brackets) and quantity produced in 1980. Including milk (2) and fruit (3) production was impossible due to no comprehensive data being available.

[8] To reduce the number of missing values especially a concern in the price data for crops the rice price is a combined measure of the paddy and rice price with the paddy price multiplied by the factor of 1.5. This is analogue to the adjustment done in the ICRISAT-dataset for combining output of paddy and rice into an overall rice output measure. Further, remaining missing values for the rice, wheat and sugar price are estimated using the median-state price of the respective crop and the price of maize and sorghum as well as district and year fixed effects. The estimated regressions have an R^2 of 0.80-0.91.

agricultural output and food prices, we also use the logarithm of agricultural wages. Finally, the share of irrigation in a district is constructed by dividing irrigated agricultural land by the total amount of land used for agriculture. Table 1 provides summary statistics for the variables of interest.[9]

2.2 Data Description

As outlined by Coffey et al. (2015), monsoon rainfall is a crucial determinant of agricultural output in India. In the following the variability of rainfall and its effect will be illustrated. Figure 1 depicts the normal distribution and the frequency of the standardized variation in monsoon rainfall by district as outlined above. Unsurprisingly, the standardized variation in monsoon rainfall by district matches the normal distribution fairly well, with extreme positive variations being slightly more likely than extreme negative variations in rainfall, while small negative deviations are more likely than positive ones.[10] From the good fit of the normal distribution it becomes clear that positive and negative variations in district monsoon rainfall away from the normal amount of more than one standard deviation (on average 243.9 mm), each occur in $\approx 15.9\%$ of years, while a variation of more than two standard deviations in either direction occurs with a likelihood of $\approx 2.3\%$.

Figure 2 depicts the effect of variations in monsoon rainfall on agricultural output. The binned scatter-plot highlights that monsoon rainfall is an important determinant of agricultural output in India. However, a more in-depth analysis of this patter using a locally weighted scatter plot smooth (LOWESS) shows that negative deviations predominantly influence agricultural output while rainfall above the norm only leads to a minimal increase in agricultural output.[11] This is well captured by a linear regression with a break-point at zero. [12]

The importance of monsoon rainfall for agricultural output, however diminishes with increased levels of irrigation. This is depicted in figure 3 in which observations are grouped by the different quantiles of irrigation that are observed in the data. The observed relationship of monsoon rainfall on agricultural output remains similar to the overall pattern in the figures depicting the relationship between monsoon rainfall and agricultural output in the lower two quantiles of irrigation-share. However, at higher levels of irrigation the clear relationship be-

[9] Table 1 highlights that monsoon rainfall accounts on average for about 64% of yearly rainfall in India.

[10] The Shapiro-Francia (1972) test cannot reject the null hypothesis of the variable being normally distributed across years for the majority of districts.

[11] When using LOWESS fitted values the regression is weighted so that the central point gets the highest weight and points that are further away receive less weight with a separate weighted regression being performed for each data point as proposed by Cleveland (1979). Obviously, variations in rainfall can be seen in this context as a purely exogenous variable, so that rainfall causes agricultural output, but agricultural output does not cause rainfall.

[12] This pattern is related to the underlying effect of water-supply on plant growth which is linear up-to a breaking point where the maximum water supply of plants is meet and the effect of additional water is zero. This break-off point has been well studied in the crop growth literature and is conceptualized in the "FAO water production function" (see e.g. Steduto et al. 2012). While the required water is differing by crop and climatic region the LOWESS estimates in figure 1 suggest that due to long-run endogenous crop selection this break-point is observable for a set of crops at the normal amount of rainfall in a district. To our best of knowledge this paper is the first in the related economic literature that accounts for this clear break-point in the effect of rainfall on agricultural output.

tween monsoon rainfall and agricultural output appears to disappear which reflects that the growth of plants does no longer depend solely on the supply of water through monsoon rainfall. Noticeable is also, that with increased irrigation agricultural productivity increases. [13] This highlights that it is crucial to account for different effects between years with above average rainfall and below average rainfall when analyzing the effect of variations in rainfall on the Indian agricultural sector. Further, it appears crucial to account for the share of irrigation in a district as it strongly decreases the dependency of agriculture on monsoon rainfall.

3 Empirical Methodology

One complication when analysing the effect of rainfall variation on the Indian agricultural sector is that variables of interest like for eaxmple agricultural output and food prices also affect each other leading to endogeneity.[14] For this reason, we use a panel-data VAR model which has the benefit of capturing the interdependencies between multiple variables without requiring the strict identification restrictions of structural models (Sims 1980).[15] This approach also captures the possible persistence of variables across years; and shows to what extent rainfall variation might have had a long-run effect on those variables. While most commonly all variables in a VAR model are treated as endogenous, it also allows for the introduction of identifying restrictions disentangling the impact of an exogenous shock - in our case the rainfall variation - onto the remaining variables (Abrigo & Love 2016). Holtz-Eakin et al. (1988) extended the original VAR framework initially applied separately on each country's time series data, see e.g. Taylor (1980), to be used in panel data settings through dealing with the possible presence of individual heterogeneity and time-series being usually much shorter in panel data.[16]

The problem with individual heterogeneity is that it violates the restriction that the underlying structure is the same for each cross-sectional unit. Note however, that including fixed effects usually used to deal with individual heterogeneity leads to the emergence of the "Nickell (1981) bias". This refers to the endogeneity problem which arises due to the correlation between the fixed effects and the lagged depended variable in datasets with a short T leading to a bias in the estimated coefficient.[17] Judson & Owen (1999) show that this issue even persists in datasets with a T as long as 30 observations. This problem can be solved by instead using

[13] This is in part also related to the fact that the overall irrigation share increases over time.

[14] For example Jayachandran (2006) studies the effect of changes in agricultural output on agricultural wages and prices, while Jacoby (2016) highlights the effect that changes in agricultural prices have on rural wages. Table 2 reports the Granger causality tests for the endogenous variables of the panel VAR showing that the included endogenous variables Granger cause each other making the use of the panel VAR necessary.

[15] A VAR can be thought of as a set of k-autoregressions, i.e. each dependent variable k is explained by its own lagged values, and the remaining k-1 variables as explanatory variables. An overview of the applications of panel VAR models in the macroeconomics and finance literature and their distinguishing features is provided in Canova & Ciccarelli (2013).

[16] Holtz-Eakin et al. (1988) also introduce the procedure of replacing missing values with zeros in the first stage of instrumental variable regressions solving the trade of between lag length and sample size in unbalanced data. Using this method the missing values in agricultural output are adequately dealt with.

[17] This obstacle in the use of panel datasets has given rise to the development of the Difference- and System-GMM estimator for panel datasets with long N and short T (see Arellano & Bond 1991; Arellano & Bover 1995; Blundell & Bond 1998). N and T denote the number of individuals and years in a panel dataset respectively.

forward mean-differencing, also known as the Helmert-transformation which removes only the forward mean (see Arellano & Bover 1995; Balestra & Krishnakumar 2008). Through this the orthogonality between transformed variables and lagged regressors is preserved which means that the lagged regressors can be used as instruments and the coefficients can be estimated by System GMM (See Anderson & Hsiao 1982; Holtz-Eakin et al. 1988; Arellano & Bover 1995; Blundell & Bond 1998; Love & Zicchino 2006).

Importantly for this approach, the 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 the cross-sectional averages are subtracted from the series tested with the aim of reducing the impact of cross-sectional dependence (Levin et al. 2002). [18] This means that the dataset meets the two major requirements for the use of the panel VAR methodology: (i) comparability and (ii) stationarity (Neumann et al. 2010). The final step before estimation is selecting the correct lag-length for the panel VAR. On the one hand, having too short lags fails to capture the system of variable's dynamic, causing an omitted variable bias. On the other hand, the lag-length being too long reduces the degrees of freedom and leads to over-parametrization. For this reason, the optimal lag-length was selected using the three consistent moment and model selection criteria developed for GMM models by Andrews & Lu (2001) which resemble the widely used maximum likelihood-based model selection criteria of Akaike (1969), Schwarz (1978) and Hannan & Quinn (1979). Following this, we set out to estimate the following second order VAR model:

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

where $Y_{n,t}$ is a four variable vector of the endogenous variables log agricultural output ($Output_{n,t}$), log agricultural wage ($Wage_{n,t}$), log food price ($Food_{n,t}$) and the irrigation share in the district ($Irrig_{n,t}$) and $X_{n,t}$ is a vector of the exogenous variables capturing the effects of variation in rainfall. In the baseline specification $X_{n,t}$ consists of a variable capturing the variation of monsoon rainfall in district standard deviations $Rain_{n,t}$ and an interaction term $Rain_{n,t} * D_{n,t}$, with the dummy variable $D_{n,t}$ being equal to 0 if $Rain_{n,t} > 0$ and equal to 1 if $Rain_{n,t} < 0$. This specification makes it possible to capture the different effect between negative and positive rainfall variation. In addition, the two monsoon rainfall variables are interacted with lagged irrigation to capture that a higher share of irrigation in a district reduces the importance of monsoon rainfall, i.e. $Rain_{n,t} * Irrig_{n,t-1}$ and $Rain_{n,t} * D_{n,t} * Irrig_{n,t-1}$. [19] A_i and B_i are the sets of coefficients which will be estimated. Finally, u_n and $e_{n,t}$ are the dependent variable specific fixed-effects and idiosyncratic errors.[20]

Roodman (2009) provides a good methodology review and practical guide to the use in STATA for single equation GMM estimation.

[18] 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) is failing to rejecting the null.

[19] We use the lagged value of irrigation here to avoid any endogeneity problems.

[20] Equation 4 reflects the specification before the Helmert-transformation has been applied (Arellano & Bover 1995).

The coefficients obtained from this empirical model are used to graph dynamic multiplier functions illustrating how a shock to one of the exogenous variables affects the remaining endogenous variables. Granger (1969) causality tests can then be used to test the statistical significance of the relationship between the included endogenous variables.[21] For the estimated impulse-response functions to be interpretable it is required that the panel VAR is invertible and possesses an infinite-order vector moving-average representation referred to as stability (Abrigo & Love 2016). The stability condition of the panel VAR is satisfied as shown in Figure 4 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 dynamic multiplier functions of the panel VAR estimation. The "baseline specification" is presented in Subsection 4.1 outlining the response of agricultural output, wages and food prices to: (i) positive rainfall variation and (ii) negative rainfall variation at different levels of irrigation. [22] Subsection 4.2 will analyse the sensitivity of the responses to positive and negative changes in rainfall to variations from the baseline specification. The following other specifications are considered: (I) we focus exclusively on rice output and prices; (II) we use the full dataset also including the districts with an altitude above 600 meters; (IV) we analyse the effect of rainfall variation in a sample excluding the districts with a rainfall standard deviation below the 10th percentile and above the 90th percentile.

4.1 Baseline Specification

Figures 5 and 6 display dynamic multiplier functions following a positive and a negative variation in rainfall at different levels of irrigation, respectively. Figure 5 shows that agricultural output responds positively to more rainfall increasing but increasing by less than 1% if monsoon rainfall increases by one standard deviation compared to the district mean. This small effect is additionally decreasing with a higher share of irrigation in a district. The effect is however not statistically significant from zero. This one standard deviation change reflects on average a 248mm increase in monsoon rainfall in a district and a similar or bigger increase in rainfall occurs on average about every 6 years. This estimate is strong contrast to the (linear) effect found by Jayachandran (2006) of $\approx 5\%$.[23]

[21] For estimation of the coefficients, IRF and Granger (1969) causality tests we use the set of STATA commands introduced by Love & Zicchino (2006) and Abrigo & Love (2016). The papers have been cited a combined 651 times to date even though the command has not been added as an official STATA command. We do not present forecast-error variance decomposition at the current stage as the contribution of exogenous variables are disregarded in the program created by Abrigo & Love (2016).

[22] While we also find significant negative effects of years with low rainfall on irrigation in the long run this does not seem of main interest to our research question.

[23] The rainfall variable used by Jayachandran (2006) reflects roughly a 1.3 standard deviation change in rainfall in our estimation. The presented values are adjusted accordingly.

The same pattern is observable for the response of agricultural wages and food prices which both are not significantly differing from zero either if the 90% confidence interval is taken into account supporting the observed pattern in Subsection 2.2 that positive variations in rainfall do not have an important effect on the agricultural sector in India. The underlying driving force of this low effect of above average rainfall on crop yield is probably the fact that crop growth depends on moisture stored in the soil as outlined in biological studies, see e.g. Richards et al. (2002), with a sufficient saturation of the soil being already reached when there are normal amounts of rainfall.

This result is in strong contrast to the effect of a reduction in rainfall observed in Figure 6. Agricultural output decreases by -21% following a decrease in monsoon rainfall by one standard deviation if the irrigation share in a district is 10%. Therefore, compared to an increase, a decrease in rainfall leads to a more than 20 times greater response in the inverse direction. Notably, the magnitude of the found effect is more than triple the size of the effect in Jayachandran (2006) who did not differentiate between positive and negative shocks. Unsurprisingly, the observed effect of a negative variation in rainfall on agricultural output is statistically significant at all common significance levels (p-value=0.00). The persistence of the shock is however fairly small reducing to a decrease in output of about -5% in the following years. This negative effect of a decrease in rainfall on agricultural output reduces as expected with increased levels of irrigation with the initial reduction being -16% (-12%) at an irrigation share of 30% (50%) in a district. This effect is however, not very persistent and the effect still observed of the rainfall shock is below -5% in the following periods with especially output in highly irrigated areas reaching nearly pre-shock levels.

Further, Figure 6 shows that agricultural wages decrease by close to -3% due to a negative shock across the depicted levels of irrigation share. As with agricultural output the effect of the reduction in monsoon rainfall decreases at increased levels of irrigation. However, the effect of local irrigation on the response of wages is much smaller. This likely relates to wages being set at an aggregate regional or country-level. [24] Interestingly, the persistence of the effect - which has not been analysed so far in the literature- is surprisingly high with agricultural wages even after 5 years being substantially lower in districts with low levels of irrigation.

Finally, Figure 6 depicts increases in food prices by 7%|6%|5% for an irrigation share of 10%|30%|50%. As in the case of wages there appears to be an aggregate component affecting the setting of prices as the effect on prices does not decrease as much as the observed effect on output with improved levels of irrigation. The effect of the shock on prices is also still observable in the following periods.

Our results are particularly interesting when compared to the contribution of Nobel Prize-winning economist Amartya Sen that famines cannot easily be explained by reductions in agricultural output, but instead that famines are caused by a breakdown in the mechanisms of food acquisition for which wages and prices play a crucial part (see e.g. Sen 1981). Our results predict very different effects on the exchange endowments of four stylized groups of individuals:

[24] Differentiating between the effect of aggregate and local changes in rainfall is the current main focus of our work.

(i) cultivators and share croppers (ii) agricultural labourers, (iii) landowners and (iv) individuals working outside the rural sector. [25] The income of cultivators and share croppers is affected by the change in agricultural output and the price they receive for their harvest in the initial period, i.e. the increase in prices compensates them in part for the loss of agricultural output. [26] Further, depending on the irrigation share in a district their income might be even higher than normal in the subsequent periods if the price increase for food outweighs the drop in agricultural output. For agricultural labourers the decrease in the agricultural wage leads to a drop in their income. Finally, landowners income is negatively affected by the drop in agricultural output, but they profit from the increased price of food and the lower wage costs that they have to pay.

The persistent decrease in agricultural wages compared to the strong recovery of agricultural output following a lean year implies that cultivators and share croppers are in particular struggling to obtain the required amount of food if there is a severe shock. However, successive shocks of identical size are not leading to a further worsening of there exchange endowment. In contrast, for agricultural workers successive years of less than normal rainfall are of particular concern as their exchange endowments will be deteriorating which each additional year of less than normal rainfall. In addition, the above presented results have shown that years of above normal rainfall do not counteract the drops in agricultural wages and increases in food prices in years with lower than average rainfall. These results indicate that the predicted increase in rainfall variability - see e.g. Dinar et al. (1998); Kripalani et al. (2007); Christensen et al. (2007) - will in particular affect the livelihoods of the poorest as they suffer the most from the variability of monsoon rainfall. [27] However, the increased usage of irrigation has dampened the negative effects of shortfalls in monsoon rain in particular in the case of agricultural output, but also to a smaller extent reducing the effect on agricultural wages and food prices. [28]

4.2 Robustness Analysis

In the following, a vast number of robustness checks is presented. Firstly, Figures 7 and 8 depicts the effect of positive and negative variations in monsoon rainfall on the output of rice, agricultural wages and the rice price, respectively. The focus on rice only has two benefits in illustrating robustness: Firstly, rice is the most important crop for nutrition and is commonly planted across the whole of India. Secondly, data on rice suffers from less missing observations

[25] Cultivators are individuals that farm on their own plot of land and earn the harvest. Share croppers get paid for their work on another persons 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.

[26] Note that prices and wages are already in real terms so that the income earned is in real terms as well. However, the fact that poorer individuals spend a higher share of income on food means that the overproportinal increases in food prices compared to other goods affects them additionally on the consumption side. This is also the case for poor individuals working outside of the agricultural sector.

[27] The projections of the climate models used by Kripalani et al. (2007) are based on the scenario of a doubling in the atmospheric CO_2 concentration. In addition to the increase in the occurrence of extreme excess and deficient monsoons, most climate models project an increase in mean rainfall which might be beneficial for agriculture if water-management improves in India.

[28] It will be interreting to see if when an aggregate shock is included the overall irrigation level in India or the respective state will reduce the effect on wages and prices strongly as well.

than the data on the other crops available in the data set so that interpolation is not required for the crop price in this case as the sample size is still big enough. The results presented in Figure 7 depicts a small increase in the output of rice if monsoon rainfall increases. This possibly relates to the fact that some districts average rainfall is below the breaking point for the water need of rice and we are observing this effect which is not significant if greater set of crops is used as done in the baseline. The high level of non-linearity in the effect of monsoon rainfall however remains the same as can be seen in Figure 8 as the drop in agricultural output is still several times greater in magnitude. The depicted wage and price responses are nearly identical between the baseline specification and the ones presented in figures 7 and 8. This suggests that our results are robust to the choice of selected crops in the baseline specification and the interpolation done for the price data.

Similar to Jayachandran (2006), we also test the sensitivity of our results to the inclusion of districts with an altitude of more than 600m. These districts were initially excluded as rainfall is expected to have a lower impact on crop yield in those districts. Figures 9 and 10 reports the corresponding response functions for a one standard deviation positive and negative variation in district rainfall. The estimated point estimates stay nearly the same and the observed confidence intervals widen slightly as we expected.

Figure 11 and 12 depicts the results after the outlier districts in terms of rainfall variation have been excluded using only the districts that lie between the 10th and 90th percentile. Surprisingly in Figure 11 an increase in rainfall has a small but significant positive effect on food prices in areas with low levels of irrigation. A possible explanation is that the increase in rainfall might affect prices through openly stored food rotting. [29] However, a further investigation of this result might be necessary. The remaining response function are similar to the baseline specification.

5 Conclusion

The contribution of this paper has been twofold. The first contribution is that the paper outlines that variations in monsoon rainfall do not have a linear effect on the agricultural sector. Instead there is a considerable difference in the magnitude of the effect between above and below average monsoon rainfall in a given year. On the one hand, abundant rainfall has nearly no effect with a one standard deviation increase in district monsoon rainfall leading to no significant change in agricultural output, wages and food prices across common levels of irrigation. On the other hand, a reduction in monsoon rainfall by one standard deviation compared to average rainfall in a district decreases agricultural output by -21%|-16%|-12% at irrigation shares in a district of 10%|30%|50%. This identified non-linear effect is in strong contrast to the previous literature which so far commonly assumed a linear effect of monsoon rainfall in India (see e.g. Jayachandran 2006; Badiani & Safir 2009; Adhvaryu et al. 2013). The found non-linear effect of monsoon rainfall has quite strong implications as it means that

[29] See for example Bajaj (2012).

years with abundant monsoon rainfall do not compensate for years with less than usual monsoon rainfall. Understanding this non-linear effect of rainfall on the agricultural sector is of particular importance considering that monsoon rainfall variations are predicted to increase further over the next decades (Challinor et al. 2006; Christensen et al. 2007).

Further, the reduction in monsoon rain also leads to drop of roughly -3% in agricultural wages declining slightly with the level of irrigation. Finally, the reduction in rainfall leads to food price increases by 7%|6%|5% for the respective irrigation shares. This leads to the second finding which is that the shock still has an effect in the consequent periods with particularly agricultural wages and food prices taking a long time to return back to the pre-shock level. In contrast the effect on agricultural output has disappeared nearly completely after one year.

These findings have strong implication for the incomes of cultivators, share croppers, agricultural workers and landowners over a long time-horizon. Landowners and especially share croppers/cultivators initially suffer a substantial income loss from shortfalls in monsoon rain. However, the negative effect on the income is short-run and might even turn positive in consequent periods. In contrast, agricultural labourers lose less income initially but the income loss is very persistent. This also means that consecutive shortfalls in rainfall especially affect agricultural labourers. In extreme cases this reduction in exchange endowments can lead to famines despite there being enough food produced.

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Appendix

A Figures

A.1 Rainfall Variation in India

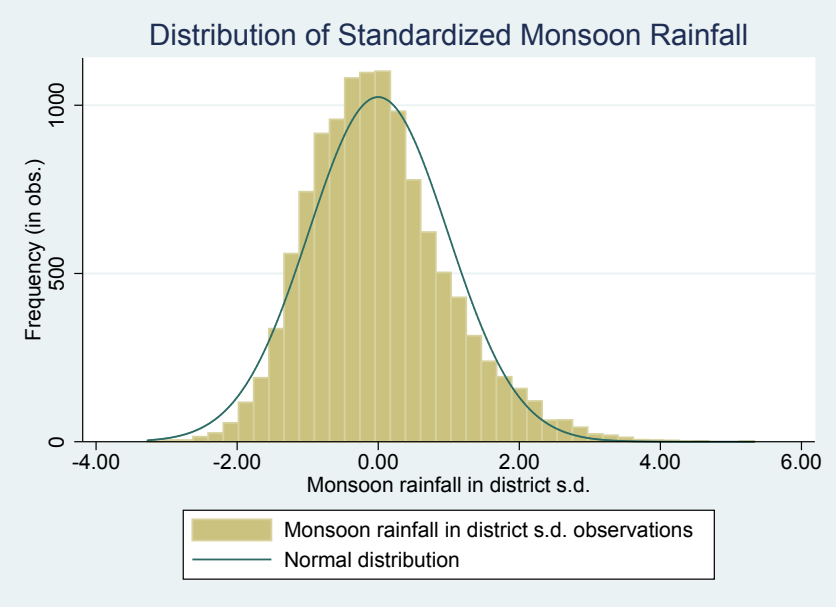

Figure 1: The figure depicts the standard normal distribution and the frequency distribution of the district standard deviation in monsoon rainfall as defined in Equation 3.

A.2 Rainfall Variation and Agricultural Output Growth

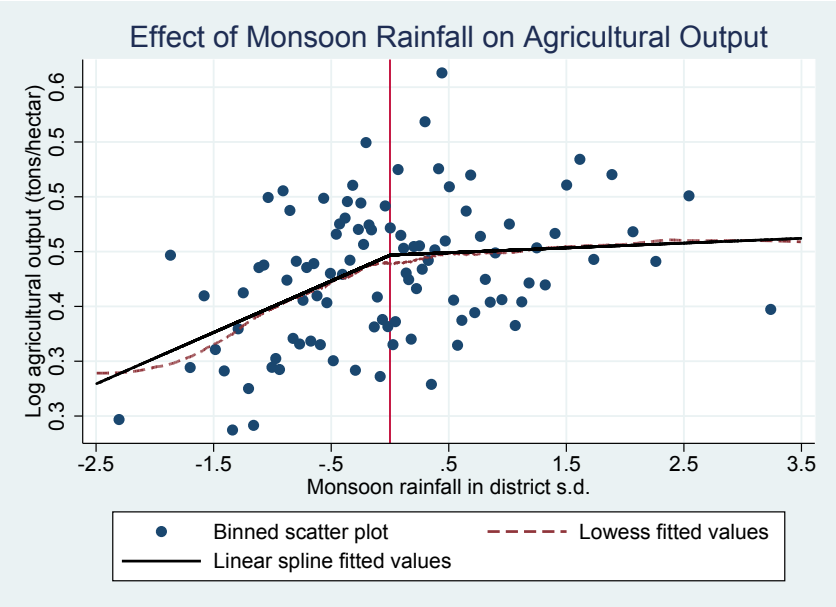

Figure 2: The figure presents a binned scatterplot (100 bins) for variations in monsoon rainfall and log agricultural output. To outline the effect of monsoon rainfall on agricultural output Locally Weighted Scatterplot Smoothing (LOWESS) and linear spline fitted values are added which have been created using the full dataset.

A.3 Rainfall Variation, Agricultural Output and Irrigation

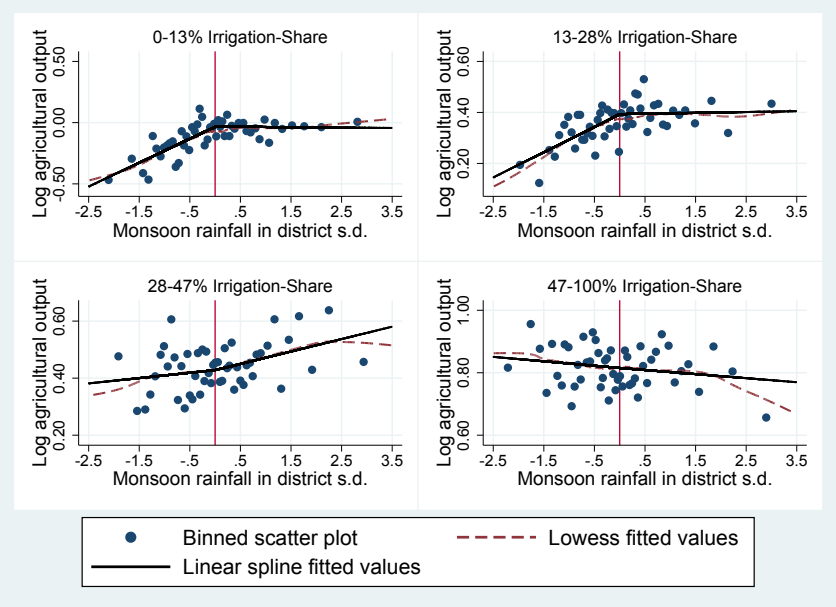

Figure 3: The figure presents binned scatterplots for variations in monsoon rainfall and log agricultural output with regards to the different quantiles of irrigation shares observed in the data. Locally Weighted Scatterplot Smoothing (LOWESS) and linear spline fitted values are added which have been created using the data of the respective irrigation-share.

A.4 Stability of the VAR

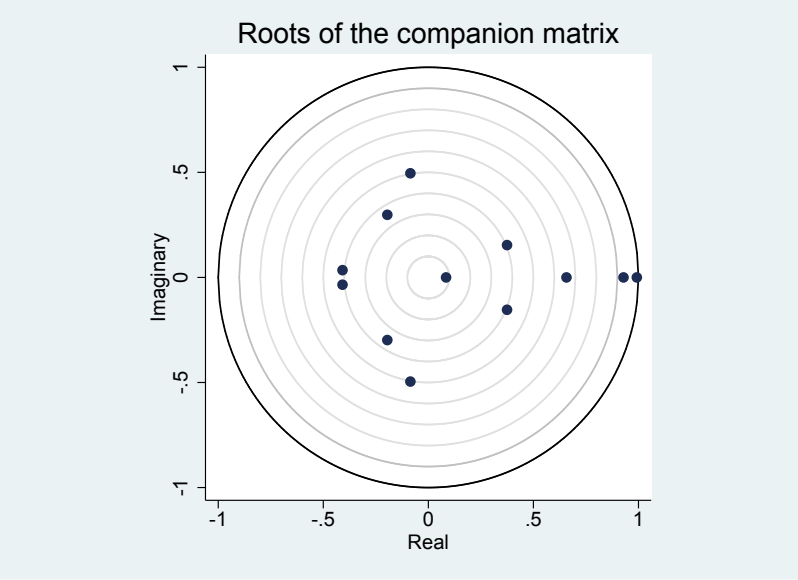

Figure 4: The graph confirms that the estimated panel VAR for the baseline specification is stable as all eigenvalues lie inside the complex unit circle.

A.5 Response to Positive Rainfall Variation

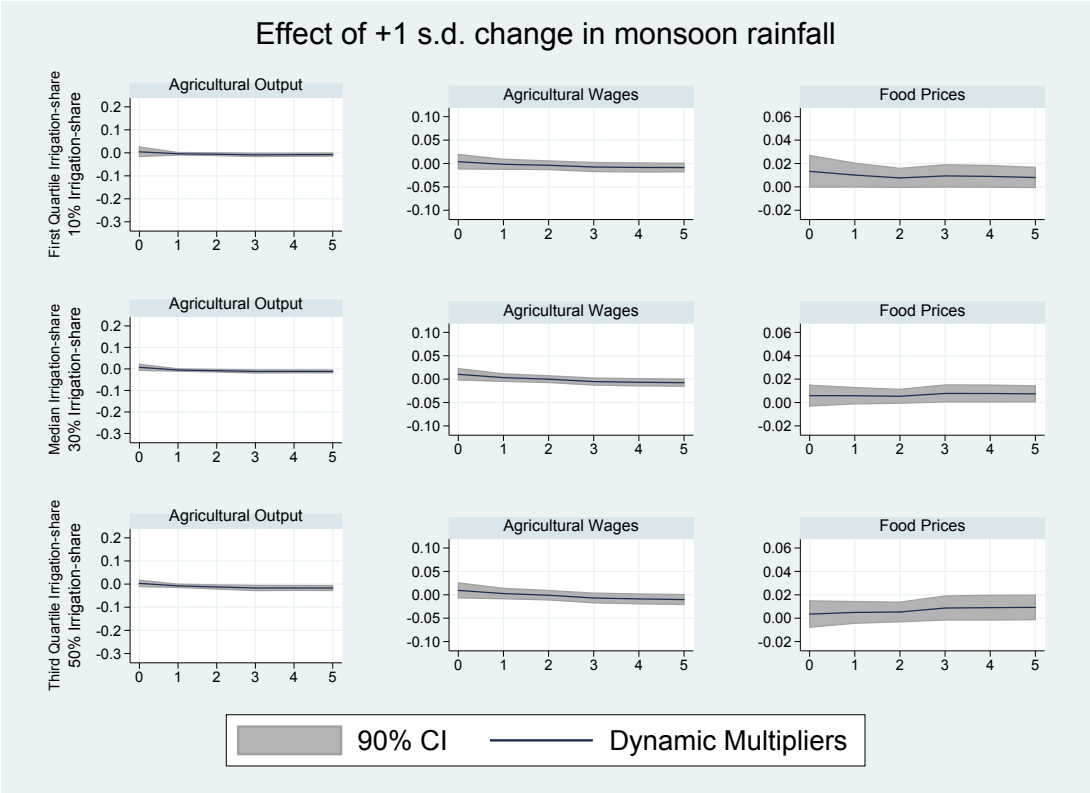

Figure 5: The figure illustrates the DM for an increase in monsoon rainfall of one district standard deviation (SD). The black solid line is the point estimate and the grey area presents the 90% confidence interval over a 5 year time period. The effect is presented for different levels of irrigation.

A.6 Response to Negative Rainfall Variation

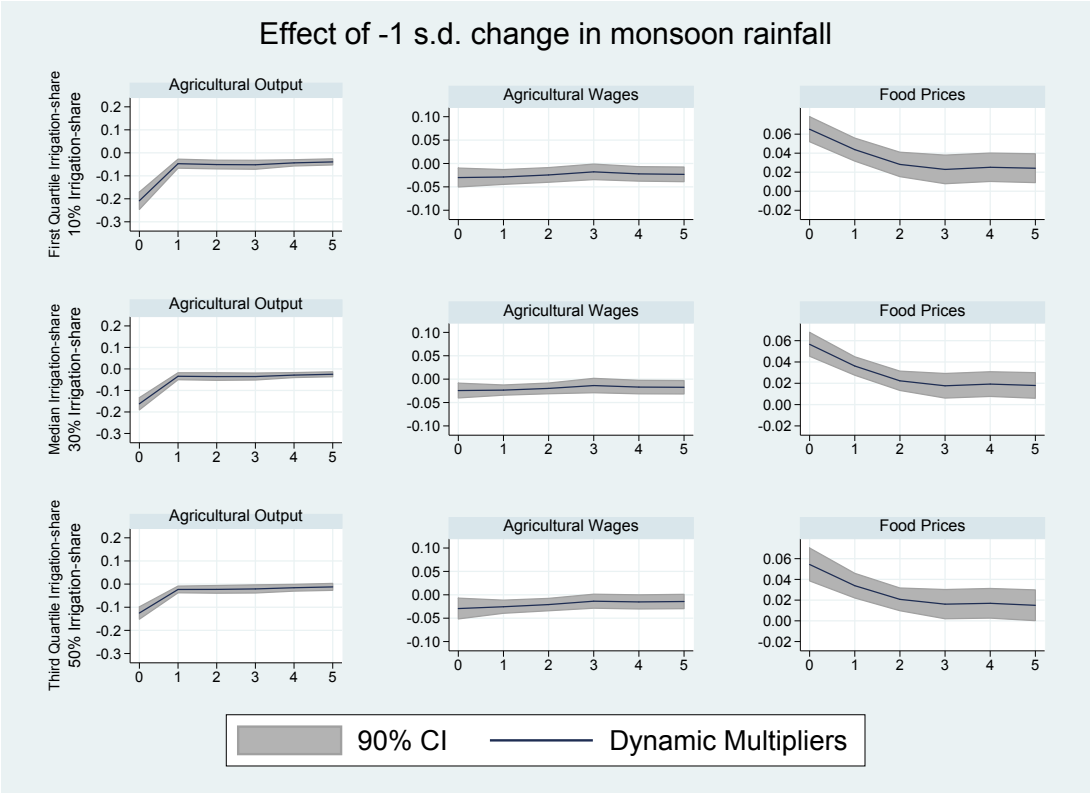

Figure 6: The figure illustrates the DM for an decrease in monsoon rainfall of one district standard deviation (SD). The black solid line is the point estimate and the gray area presents the 90% confidence interval over a 5 year time period. The effect is presented for different levels of irrigation.

A.7 Robustness: Rice Responses

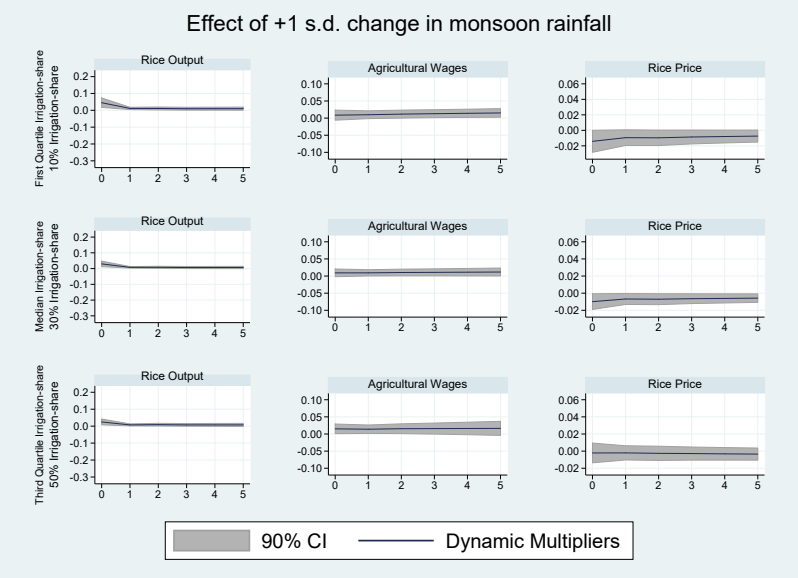

Figure 7: The figure depicts the responses to an increase in rainfall when the rice price (not interpolated) and output are used as variables instead of a measure of combined agricultural output and a food price index.

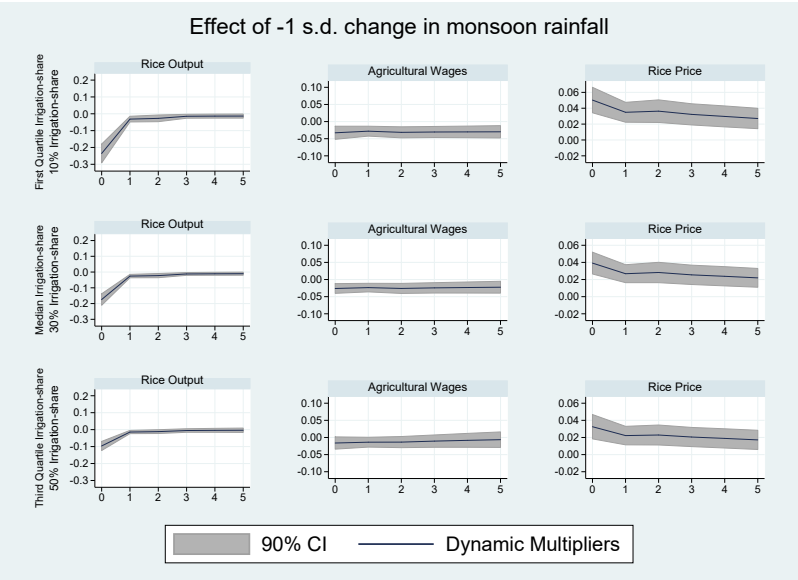

Figure 8: The figure depicts the responses to an decrease in rainfall when the rice price (not interpolated) and output are used as variables instead of a measure of combined agricultural output and a food price index.

A.8 Robustness: High Altitude Districts Included

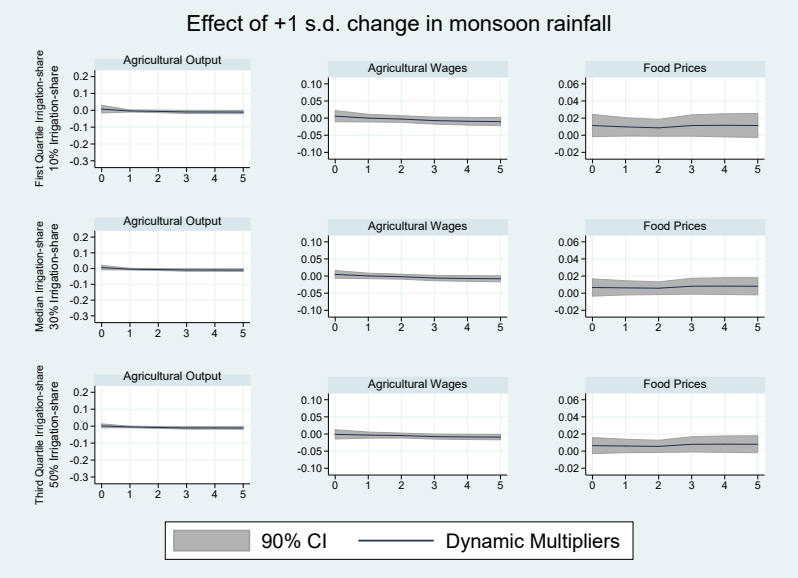

Figure 9: The figure depicts the responses to an increase in rainfall when districts with an altitude above 600m are included in the dataset.

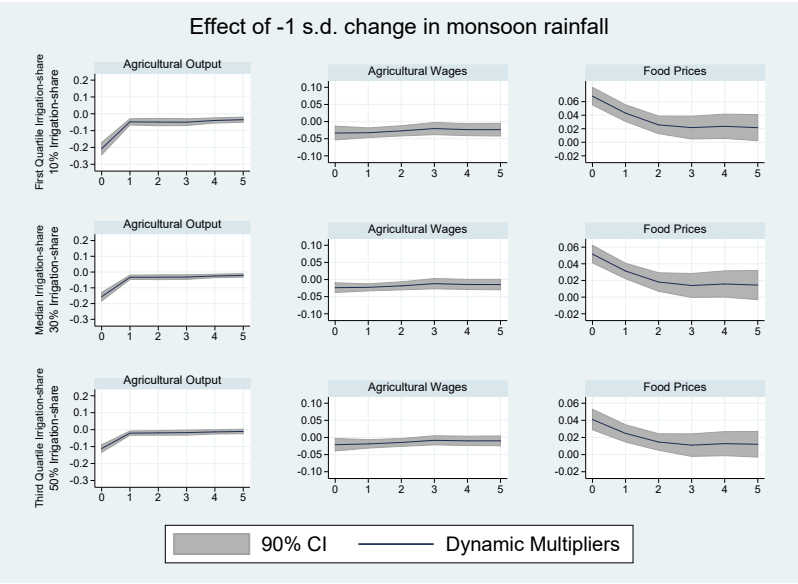

Figure 10: The figure depicts the responses to an decrease in rainfall when districts with an altitude above 600m are included in the dataset.

A.9 Robustness: Exclusion of Outliers

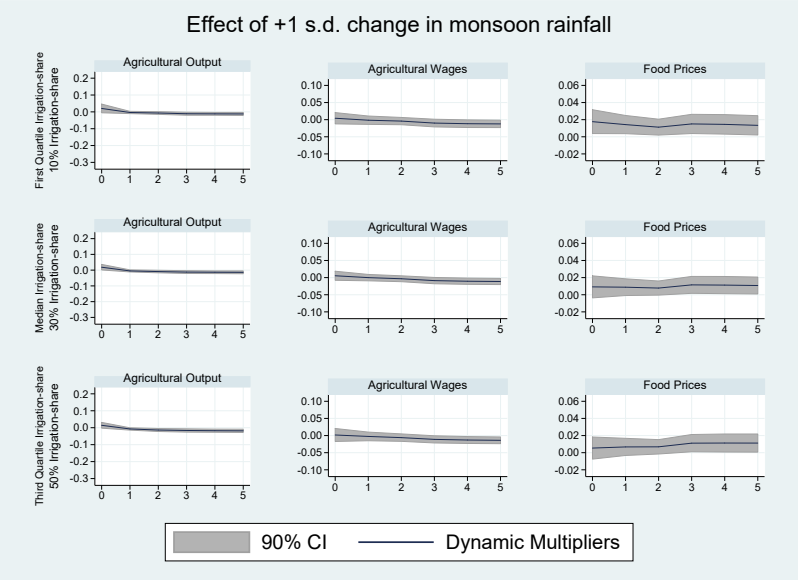

Figure 11: The figure illustrates the IRF point estimates and 90% confidence intervals for an increase and decrease in monsoon rainfall of one district standard deviation (SD) when districts with a rainfall variation below the 10th and above the 90th percentile are excluded from the dataset.

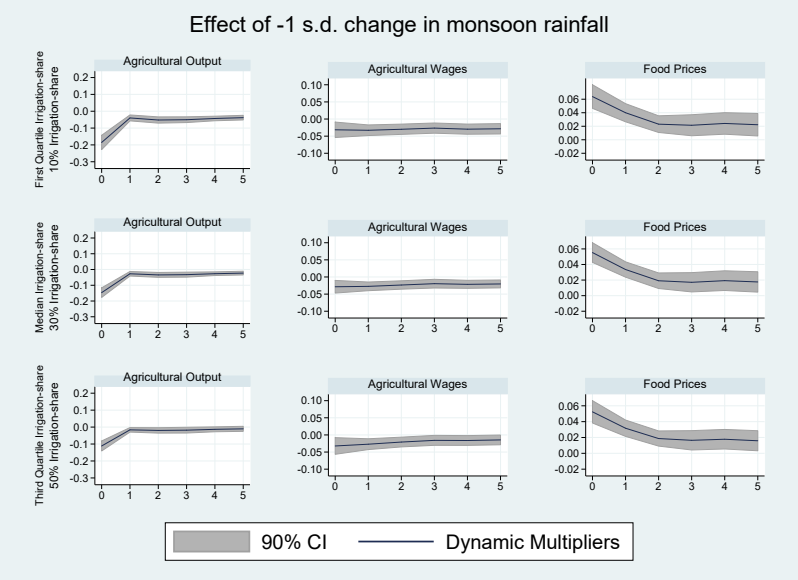

Figure 12: The figure illustrates the IRF point estimates and 90% confidence intervals for an increase and decrease in monsoon rainfall of one district standard deviation (SD) when districts with a rainfall variation below the 10th and above the 90th percentile are excluded from the dataset.

B Tables

B.1 Summary Statistics

	Mean	Standard Deviation	Observations
Rainfall Variables:			
Annual rainfall (in mm)	1114.17	713.96	12,066
Monsoon rainfall (in mm)	709.97	515.03	11,950
Monsoon rainfall in district s.d.	0.00	0.99	11,947
Agricultural Output Variables:			
Rice output (tons/hectar)	1.50	0.84	11,618
Wheat output (tons/hectar)	1.64	0.86	10,598
Sugar output (tons/hectar)	5.38	2.97	10,681
Log agricultural output	0.44	0.54	8,785
Food Price Variables:			
Rice price (real INR/100kg)	14.26	6.39	8,694
Wheat price (real INR/100kg)	14.38	4.00	7,826
Sugar price (real INR/100kg)	21.24	8.33	5,796
Log price index	2.61	0.29	8,632
Other Variables:			
Agricultural Wage (real INR)	0.85	0.46	8,967
Log agricultural wage	-0.27	0.45	8,967
Share of irrigated Land	0.34	0.25	11,140

Table 1: This table presents descriptive statistics for the variables used in the baseline specification or from which they are constructed. In all graphs and estimations the logarithm of agricultural output, agricultural wages and the food price index is used. INR stands for Indian Rupee.

B.2 Granger Causality Tests

Excluded / Equation	Output	Wage	Price	Irrigation
Output		0.01	0.00	0.62
Wage	0.00		0.87	0.63
Price	0.00	0.00		0.03
Irrigation	0.00	0.02	0.00	
All	0.00	0.00	0.00	0.06

Table 2: The table reports the Granger causality tests with the null hyphothesis being that the excluded variable does not Granger-causes the equation variable, while the rejection of the null hypothesis means that the excluded variable Granger-causes the equation variable.

C Data Appendix

The shapefile for 1966 has been created using the depiction of census boundaries in 2001 from Census of India (2011) and the information on district changes from 1961-2001 from Kumar & Somanathan (2015).