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The dynamic effects of monsoon rainfall shocks on agricultural yield, wages, and food prices in India*

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Abstract

This paper shows that, first, the effects of monsoon rainfall shocks on agricultural yield in India are highly asymmetric: yield falls strongly after droughts, whereas excessive rainfall has only little effects. Second, our key novel finding is that the short-lived yield loss after a widespread drought elicits a persistent decline (increase) in wages (food prices), which lasts for up to five years. Third, affiliation to the same National Sample Survey region (and thus to the same state) seems to be a key determinant of internal migration, whereas distance appears more relevant for food arbitrage trading.

Keywords: Agricultural yield; food prices; rainfall shocks; wages

JEL classification: C33; E32; O13; Q11

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1. Introduction

“Much in India’s economy depends on the monsoon. Farming is India’s largest employer. Three-fifths 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%.” (Source: *The Economist*, Inflation in India: of rainfall and price rises, 25 June 2015)

India accounts for almost 20 percent of the world’s population and (still) about 50 percent of the Indian workforce is employed in the agricultural sector (Cagliarini and Rush, 2011). Despite huge productivity advances, mainly as a result of the introduction of high-yield seeds, the increased use of fertilizers, and improvements in irrigation (commonly referred to as the Green Revolution; see International Food Policy Research Institute 2002), a large share of the rural population still lives in precarious conditions and hence is vulnerable to income and food price uncertainty (see e.g., Fan et al., 1998; Himanshu, 2007; Iyengar and Viswanathan, 2011). The most important source of (economic) uncertainty in rural India is the variation in monsoon rainfall (Coffey et al., 2015). Using a static framework, Jayachandran (2006) shows that droughts depress the wages of agricultural labourers.¹ Further, recent evidence by Boffa and Varela (2019) and Kaur (2019) additionally points to an important role of price and wage rigidities.² Therefore, the main aim of the current paper is to revisit the impact of monsoon rainfall shocks using a dynamic framework, which captures their – potentially long-lasting – effects that arise from sluggish price and wage responses.

Whilst Jayachandran (2006) is the paper most closely related ours, we contribute to the literature in the following ways. First, we distinguish between positive and negative monsoon rainfall shocks to account for their asymmetric effects. Second, we estimate a panel vector autoregression (VAR) – based on data from 310 Indian districts over the period 1967–2005 – to capture the persistent effects of monsoon rainfall shocks on agricultural yield, wages, and food prices. Third, we control for the spatial dimension (local/regional) of rainfall shocks in order to study the potentially moderating effects of arbitrage trading and migration on food prices and wages, respectively.

¹ Other related contributions in this field include, for example, Mooley and Parthasarathy (1982), Adams (1989), Paxson (1992), Rosenzweig and Wolpin (1993), and Mueller and Osgood (2009).

² Notably, Jacoby (2016) highlights that in certain cases (e.g., rising international demand) increasing food prices might also benefit rural households.

This paper shows that the effects of monsoon rainfall shocks on agricultural yield in India are indeed highly asymmetric: depending on the local extent of irrigation, yield falls by up to 30 percent (15 percent) after a regional (local) drought, whereas positive rainfall shocks have only little effects.³ In particular, the estimated yield loss after negative monsoon rainfall shocks turns out to be two to three times higher than estimates based on conventional symmetric approaches. Moreover, our key novel finding is that the short-lived yield loss after a regional drought elicits a persistent decline (increase) in wages (food prices). Wages fall by up to 7 percent, with the peak decline occurring two years after the drought and lasting up to five years. Food prices immediately rise by up to 5 percent, and remain at elevated levels for up to two years. The local extent of irrigation dampens the fall in agricultural wages after a regional drought, but not the rise in food prices. Local droughts, instead, only affect agricultural wages (depending on the extent of local irrigation), whereas food prices remain unaffected. Moreover, we find that affiliation to the same National Sample Survey (NSS) region (and thus to the same state) seems to be a key determinant of internal migration, whereas distance appears more relevant for food arbitrage trading.

In addition, we argue 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 (Kaur, 2019). However, in the medium run, their income deteriorates in *real* terms – owing to the persistent decline in wages and the persistent rise in food prices. This combination is particularly harmful to the rural poor in the face of incomplete credit markets (see Lanjouw and Shariff, 2004; de Janvry and Sadoulet, 2009), and thus might explain why famines (or, more generally, hunger) are generally considered to be caused by the unaffordability rather than the unavailability of food, and they can occur after agricultural output already started to recover (Sen, 1981).⁴ Cultivators suffer from the short-term drop in agricultural yield, but can gain from the medium-term rise in prices for agricultural yield that is not used for own consumption. As a result, subsistence farmers that produce less for the market are more severely affected.⁵

The remainder of this paper is structured as follows. In Section 2, we present the data and the data sources. In Section 3, we outline the empirical

³The stronger impact of regional droughts relative to local droughts can be attributed to the fact that regional droughts tend to arrive in the months most crucial for crop yield (see also Bhandari et al., 2007).

⁴Even 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 has remained a serious problem (Banik, 2006).

⁵See Gollin and Rogerson (2014) for a model on the determinants of subsistence farming.

methodology. In Section 4, we discuss the results. Finally, we conclude in Section 5.

2. Data sources and description

2.1. Data sources

We construct a panel that comprises annual data from 310 Indian districts (defined by 1966 boundaries) between the years 1967 and 2005. This panel builds largely on the dataset of ICRISAT (2016), which provides district-level data on prices of agricultural products, produced quantities, wages in the agricultural sector, cultivated land area, and the share of irrigated cultivated land.⁶

To measure agricultural yield during the summer monsoon (kharif) season (June–October),⁷ we take into account the produced quantities of the following commodities: rice, sugar, sorghum, millet, maize, and groundnut, as well as the corresponding cultivated land area. More precisely, agricultural yield is defined as the natural logarithm of the amount produced in tons per 1 km² for the selected crops, weighted by the cultivated land area:

$$Yield_{n,t} = \frac{\sum_i Area_{i,n,t} * \log(Quantity_{i,n,t} / Area_{i,n,t})}{\sum_i Area_{i,n,t}}. \quad (1)$$

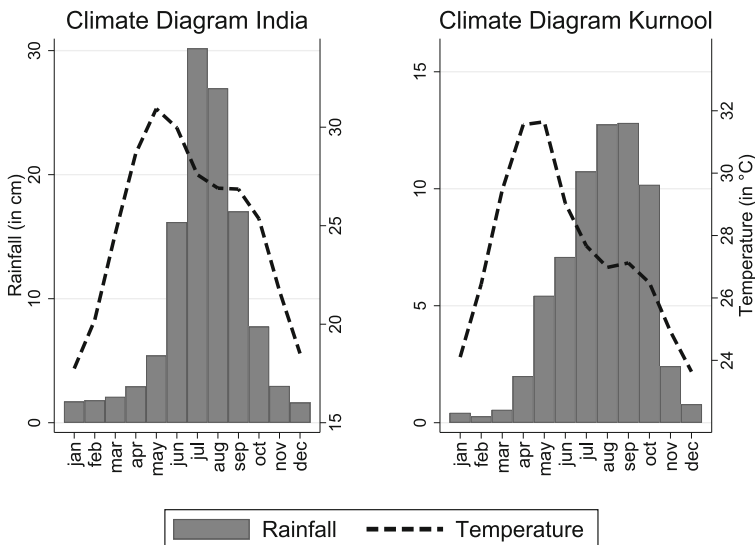
Here, i denotes the crop type, t is the year, and n is the district. Analogously, we weight the natural logarithm of nominal crop prices (measured at the farm gate) to construct an index of food prices at the district level.⁸

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

⁶We exclude all observations before 1967 due to numerous outliers; we correct misreported prices (by an order of magnitude) before 1970 in 11 districts; and we set all observations for prices and wages that are reported “0” to “missing”. The end of our sample marks the introduction of the National Rural Employment Guarantee Act (NREGS) of 2005 (start of implementation: April 2006). Rosenzweig and Udry (2014) find that the NREGS helped to stabilize wages in areas affected by bad weather shocks, whereas Maitra and Tagat (2019) study within-household time allocation decisions in response to rainfall shocks in the post-NREGS period. We thus also exclude the period of sharp increases in international food prices (2007–2008), which led the Indian government to impose export bans and other measures on several agricultural commodities (Jacoby, 2016).

⁷The length of the kharif season varies by crop and by state, but is typically considered to last from June to October. Rainfall in the months of July and August accounts for almost 60 percent of summer monsoon rainfall and for nearly half of annual rainfall in our sample period (but variation across districts is large; see Figure 1).

⁸Depending on the cost structure and mark-ups of food intermediaries, variations in farm prices lead to more or less amplified movements in consumer prices.

Figure 1. Climate diagrams for the whole of India (left panel) and the Kurnool district in Andhra Pradesh (right panel)

Source: Authors' calculations for the period 1967–2005 based on Willmott and Matsuura (2012).

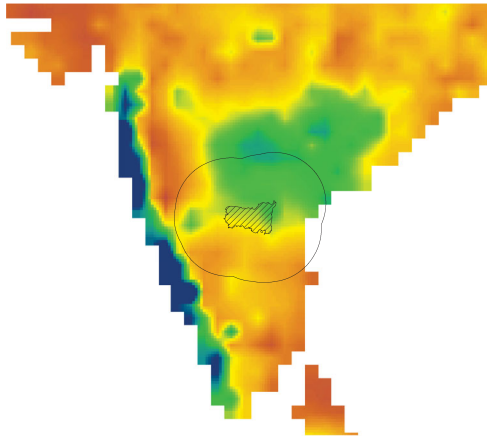
In addition, we use the natural logarithm of male wages in agriculture (in Rupees per day, averaged over the agricultural year) and the share of irrigated cultivated land, which is constructed by dividing the irrigated cultivated land area by the total cultivated land area.⁹

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 and Matsuura (2012). More precisely, for each district, we subtract mean summer monsoon rainfall (in centimeters) from actual summer monsoon rainfall, and then divide the difference by the corresponding standard deviation (similarly to Cole et al. 2012):¹⁰

$$Rain_{n,t} = \frac{monsoon\ rainfall_{n,t} - \overline{monsoon\ rainfall}_n}{\sqrt{E[(monsoon\ rainfall_{n,t} - \overline{monsoon\ rainfall}_n)^2]}}. \quad (3)$$

⁹Because of the limited availability of female wages in agriculture, we restrict our sample to male wages.

¹⁰This 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). We also explore the potential role of long-run developments in rainfall across all districts. However, we find little support for any nationwide pattern.

Figure 2. Buffer area illustration

Notes: The figure depicts the Kurnool district in the state of Andhra Pradesh with an area of 17,626 km² (shaded area). The average size of an Indian district is about 10,000 km². The area surrounding the district is the 200 km buffer area. The areas are calculated using a projected coordinate system – a two-dimensional approximation of the Earth's surface – of the Indian subcontinent. The underlying data illustrate the amount of rainfall in August 2000, which is used for constructing rainfall in districts and buffer areas.

We thus take into account that farmers in districts with below-average rainfall tend to plant crops that require less water and vice versa, and that farmers in districts with high rainfall variation usually plant crop strains and use technologies that reduce the sensitivity of yield to rainfall variations (Pandey and Bhandari, 2007). Second, for each district, we standardize summer monsoon rainfall also for a region that comprises the district area itself and a surrounding buffer zone of 200 km. In the stylized case of a circle with a radius of about 56 km and an area of 10,000 km² (according to the average size of an Indian district), the circular area corresponds to about 5 percent of the constructed regional area (see Figure 2, which also shows the underlying rainfall grid).^{11,12} Third, we regress district-wise standardized rainfall on region-wise standardized rainfall:

¹¹ 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 buffer zones of 150 km or 300 km. The only noteworthy change is that, with a buffer zone of 300 km, 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.

¹² Georeferenced data for agricultural yield, wages, and food prices are unfortunately not available.

Table 1. Descriptive statistics

	Mean	Std dev.	Observations
Rainfall variables			
Annual rainfall (in cm)	116.62	67.00	12,089
Monsoon rainfall (in cm)	98.08	56.66	12,089
Monsoon season rainfall SD.	0.00	0.99	12,089
Local monsoon rainfall SD.	0.00	0.59	12,089
Regional monsoon rainfall SD.	0.00	0.79	12,089
Agricultural sector variables			
Log agricultural yield (ton per km ²)	4.69	0.69	10,643
Log agricultural wage (Rupees)	2.44	1.15	8,877
Log price index (Rupees per ton)	7.66	0.78	8,526
Other variables			
Share of irrigated land	0.33	0.25	11,070
Monsoon temperature (demeaned)	0.00	0.46	12,089

Notes: Mean, standard deviation, and number of observations are shown.

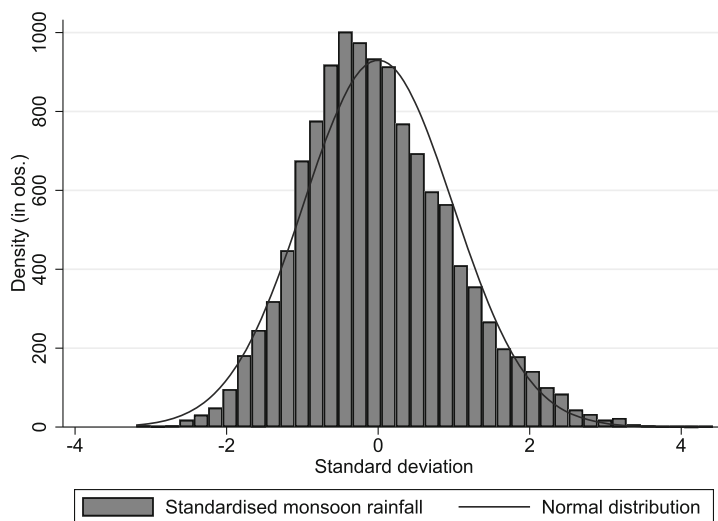
$$\underbrace{Rain_{n,t}}_{\text{standardized rainfall}} = \underbrace{\hat{\beta}Rain_{n200,t}}_{\text{regional component}} + \underbrace{\epsilon_{n,t}}_{\text{local component}}$$

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

2.2. Data description

Monsoon rainfall in the kharif season is a crucial determinant of agricultural yield in India (Coffey et al., 2015). To illustrate its variability, Figure 3 depicts a histogram of 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.¹³ Given the good fit of the normal distribution,

¹³For the majority of districts, the Shapiro and Francia (1972) test cannot reject the null hypothesis of normal distribution across years.

Figure 3. Illustration of rainfall distribution in India

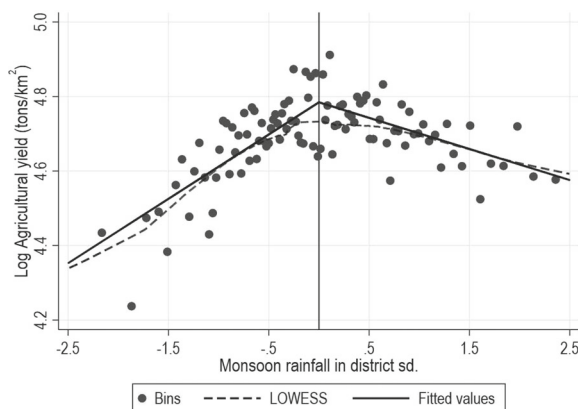
Notes: Normal distribution and distribution of standardized monsoon rainfall, as defined in equation (3).

positive/negative variations of more than one standard deviation occur in about 16 percent of years, while the relative frequency of deviations of more than two standard deviations is roughly 2.3 percent.

Figure 4 illustrates the effects of variations in monsoon rainfall on agricultural yield using a binned scatterplot. To highlight the non-linear relationship, we also present the fitted curve generated by a locally weighted scatterplot smooth (LOWESS) regression.¹⁴ The LOWESS curve indicates that negative deviations in standardized rainfall reduce agricultural yield substantially, while rainfall above the district-mean reduces agricultural yield only slightly. This pattern is also well captured by a linear regression with a break point at mean district-level rainfall.¹⁵ These non-linear effects render

¹⁴In a LOWESS regression, a weighted regression is carried out for each binned observation, where the central observation receives the highest weight and more remote observations receive less weight (Cleveland, 1979).

¹⁵This 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 to endogenous crop selection in the long run, this break point is close to mean standardized rainfall.

Figure 4. The impact of overall rainfall variation on agricultural yield

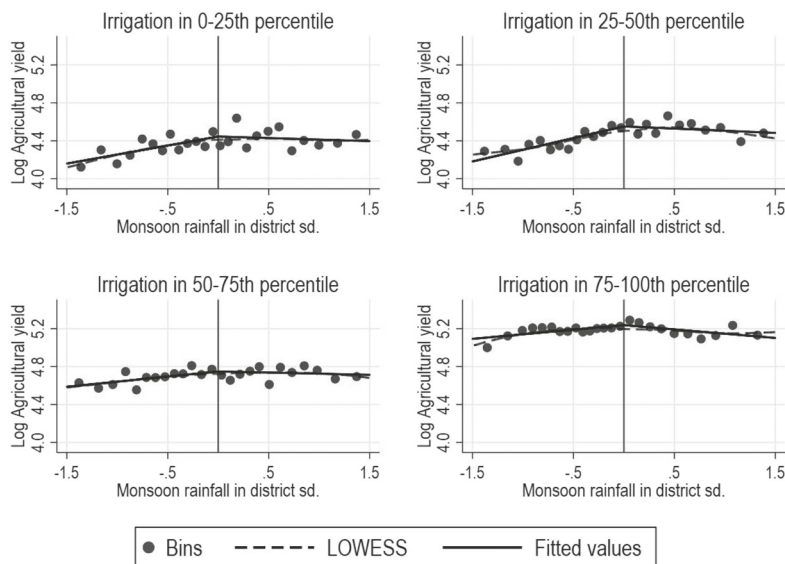
Notes: The scatterplot shows 100 bins with ~104 observations each for depicting variations in overall monsoon rainfall and log agricultural yield. To outline the effect of monsoon rainfall on agricultural yield, LOWESS and linear spline fitted values are added (these values have been created using the full dataset, while for illustration purposes the x -axis has been restricted to the range from -2.5 to 2.5).

consumption smoothing more challenging, and imply that rainfall shocks are no longer distributionally neutral in the long run.¹⁶

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

¹⁶Alternatively, we constructed a district-specific measure of optimal rainfall, based on crop-specific optimal rainfall from Steduto et al. (2012) and weighted by cropping area. However, even after controlling for outliers, we note that the kink at zero deviation from optimal rainfall is less distinct than in Figure 4 and the point cloud is much more dispersed – which likely reflects that the reported values in Steduto et al. (2012) do not capture well the changing optimal water requirements of local crop varieties at different points in time. For instance, between the years 1970 and 1990, the use of high-yielding varieties (HYVs) spread widely in India (see, e.g., International Food Policy Research Institute, 2002). These HYVs typically require even less water than local varieties, but tend to be more sensitive to variation in water supply (Dalrymple, 1976). Other approaches include Guiteras (2009) and Cole et al. (2012), who capture the non-linearity by including a squared term for rainfall, and Kaur (2019), who distinguishes explicitly between positive and negative rainfall shocks, defined as realizations above (below) the 80th (20th) percentile of the district-specific distribution.

Figure 5. The impact of overall rainfall variation on agricultural yield at different levels of irrigation



Notes: Each scatterplot shows 25 bins for depicting variations in overall monsoon rainfall and log agricultural yield at different percentiles of irrigation. The figure also shows LOWESS and linear spline fitted values.

Moreover, we decompose rainfall shocks along the spatial dimension (see Section 2.1). Regional and purely local rainfall shocks can exert different effects on food prices and wages, which allows us to infer to what extent their adverse effects can be mitigated by arbitrage trading and migration. In addition, we find that regional rainfall shocks are not randomly distributed across the monsoon season, but tend to arrive in the months most crucial for crop yield.¹⁷ In particular, the coefficients of determination in Panel A of Table 2 show that the contribution of regional rainfall shocks to the variance

¹⁷Bhandari et al. (2007) attribute the higher sensitivity of crop yield to moisture stress in the late kharif season to the facts that this period corresponds to the crucial reproductive and grain-filling stage, and that the late kharif season leaves less opportunities for crop management than the early kharif season (for instance, by replanting or resowing). For this reason, late (early) season droughts reduce agricultural output mainly through a lower crop yield (smaller cultivated land area). The view that the late kharif season is more crucial is shared by Redfern et al. (2012), based on experimental evidence presented in Liu et al. (2006), by Chhinh and Millington (2015), based on evidence from Cambodia, by Kattelus et al. (2015), based on evidence from the Ganges–Brahmaputra–Meghna region, and by Moonmoon and Islam (2017), also based on experimental evidence. Fischer and Fukai (2003) document how rice plants respond to drought in different seasons/growth stages.

Table 2. Spatial dimensions of overall rainfall variation for each month over the kharif season, and their importance for annual crop yield

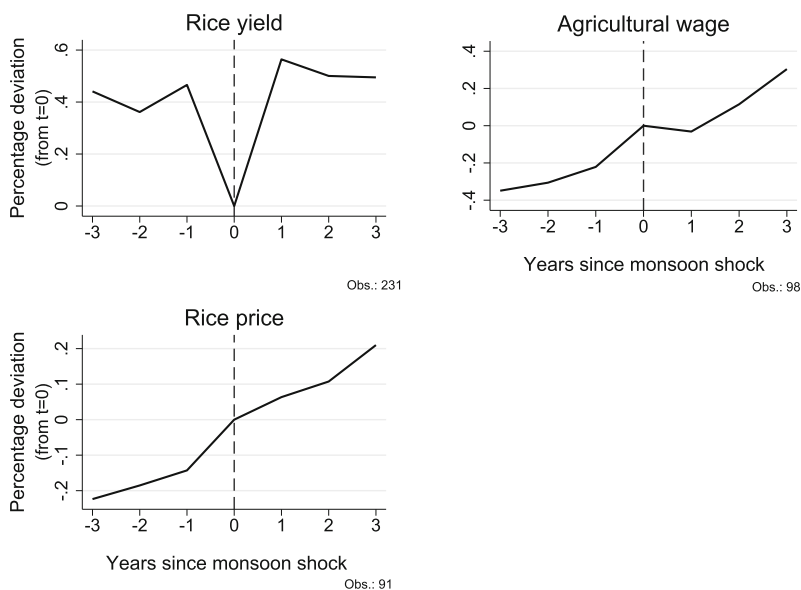
	June	July	August	September	October
Panel A. Monthly standardized rainfall on monthly regional rainfall					
Coefficient	0.87***	0.84***	0.81***	0.88***	0.91***
Standard error	(0.01)	(0.00)	(0.01)	(0.00)	(0.00)
R^2	0.75	0.70	0.65	0.77	0.83
Observations	12,089	12,089	12,089	12,089	12,089
Panel B. Annual agricultural yield on monthly standardized rainfall					
Overall rainfall	0.028***	0.005	0.000	0.042***	0.043***
Standard error	(0.004)	(0.005)	(0.006)	(0.005)	(0.004)
Within R^2	0.005	0.000	0.000	0.010	0.011
Observations	10,643	10,643	10,643	10,643	10,643
Panel C. As in Panel B, but separately for negative and positive shocks					
Negative rainfall	-0.095***	-0.023**	-0.071***	-0.139***	-0.135***
Standard error	(0.011)	(0.009)	(0.012)	(0.010)	(0.010)
Positive rainfall (interaction term)	0.105***	0.030**	0.120***	0.157***	0.134***
Standard error	(0.015)	(0.013)	(0.015)	(0.014)	(0.014)
Within R^2	0.010	0.001	0.007	0.022	0.018
Observations	10,643	10,643	10,643	10,643	10,643

Notes: Panel A shows the results for univariate regressions of monthly standardized rainfall on monthly regional rainfall. Panel B presents results for univariate regressions of annual agricultural yield on monthly standardized rainfall (both demeaned at the district level). Panel C displays the results when the coefficients are allowed to vary between negative and positive rainfall shocks. Note that the coefficients for the variables “negative rainfall” can directly be interpreted as the effect of a one-unit decrease in overall standardized rainfall for the respective month. To obtain the corresponding effect of a one-unit increase in overall standardized rainfall, the coefficients of the variables “negative rainfall” and “positive rainfall” need to be summed up and multiplied by -1 . Importantly, we do not control for any time-fixed effects in the regressions, as these would also capture the impact of regional rainfall variation. District-level clustered standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

in overall standardized rainfall in June, September, and October is 75 percent, 77 percent, and 83 percent, respectively – whereas, in July and August, their contribution is clearly lower (70 percent and 65 percent, respectively).¹⁸ Furthermore, Panel B of Table 2 shows that annual agricultural yield responds much more sensitively to overall rainfall variations in the months June, September, and October than to mid-season variations.¹⁹

¹⁸Panel A of Table 2 shows that the estimated coefficients of month-by-month univariate regressions of standardized rainfall on regional rainfall are all (except for the June and September values) significantly different from each other. The relative contribution of regional rainfall to overall standardized rainfall variability – given by the coefficient of determination – is a linear transformation of the estimated coefficient.

¹⁹See Panel C of Table 2 for separate estimates in response to negative and positive rainfall shocks.

Figure 6. Quasi-event study visualization of drought impact on yield, wages, and prices

Notes: 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 one standard deviation has occurred. Only balanced data are used for plotting the graphs.

Beyond the impact on agricultural yield, the main aim of our paper is to understand the link between monsoon rainfall shocks and the livelihoods of the population in rural India. As argued by Sen (1981), famines – or, more generally, hunger – are not only due to the (direct) shortfall in agricultural yield, but rather to the (un)affordability of food. Thus, the dynamics of income and food prices play a key role here. Figure 6 illustrates the transmission mechanism in a quasi-event study setting – that is, it plots averaged raw data for agricultural yield, wages, and food prices across districts before, during, and after a severe negative rainfall shock.²⁰ We observe that such a shock leads to a sharp decline in rice yield (the main agricultural crop).²¹ However, in the year after the shock, rice yield returns quickly back to its pre-shock level. Initially, nominal agricultural wages do not appear to be affected at

²⁰More precisely, we study the effects of a reduction in overall standardized rainfall by at least 1.5 units. In addition, we require that no other negative/positive shock of more than one standard deviation has occurred in a window of \pm three years around the negative shock.

²¹Given that only very few negative monsoon rainfall shocks meet these criteria, we use rice yield and prices instead of the composite measures to maximize the available sample size in this exercise.

all. However, in the year after the negative shock, wage growth is stagnant (i.e., wages do not even adjust for inflation). This finding is in line with the degree of downward nominal wage rigidity observed by Kaur (2019). In addition, the figure 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. The rice price, however, increases in the year of the shock and remains at levels above its pre-shock trend for more than two years. In order to capture the lasting impact on monsoon rainfall shocks on income and food prices, we examine its dynamic effects more formally using an estimated panel VAR.

3. Empirical methodology

The main aim of this paper is to identify the dynamic effects of exogenous variations in monsoon rainfall shocks on yield, wages, and prices in the Indian agricultural sector, as well as the interdependences between these variables.²² For this purpose, we estimate a panel VAR based on data from 310 Indian districts (Holtz-Eakin et al., 1988; Abrigo and Love, 2016).²³ To control for unobserved heterogeneity at the district level, we apply the Helmert transformation (see Nickell, 1981; Arellano and Bover, 1995; Balestra and Krishnakumar, 2008).²⁴ 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, and changes 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 and Mairesse (2005). The outcome of the tests is the same when first cross-sectional averages are subtracted from the series (with the aim of reducing the impact of cross-sectional dependence; see Levin et al. 2002).²⁵

²²Related to our work, Jayachandran (2006) studies the static effects of changes in agricultural yield on agricultural wages and prices, whereas Jacoby (2016) examines the effects of changes in agricultural prices on rural wages.

²³VAR models capture the interdependences between multiple variables with less strict identification restrictions than structural models, as well as the (potentially persistent) effects of structural shocks (Sims, 1980). See Canova and Ciccarelli (2013) for an overview on the range of applications of panel VAR models in macroeconomics and finance.

²⁴This 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 generalized method of moments (see Arellano and Bond, 1991; Arellano and Bover, 1995; Blundell and Bond, 1998; Judson and Owen, 1999; Love and Zicchino, 2006).

²⁵For the irrigation-share variable, only the unit-root test of Im et al. (2003) suggests stationarity. The unit-root test by Breitung (2000) fails to reject the null. For this reason, the irrigation share is included in first-differences. Results are overall similar when irrigation is included in levels as an endogenous variable, but the pattern of some impulse responses appears less smooth.

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, I . Based on the outcome of the Andrews and Lu (2001) lag-length selection criterion, we set out to estimate the following third-order ($I = 3$) VAR:²⁶

$$Y_{n,t} = \sum_{i=1}^I \alpha_i Y_{n,t-i} + \sum_{i=0}^I \beta_i X_{n,t-i} + \gamma_n + \eta_{s,t} + e_{n,t}, \quad (4)$$

where

$$\begin{aligned} Y_{n,t} &= [Yield_{n,t}, Wage_{n,t}, Food_{n,t}, \Delta Irrig_{n,t}], \\ X_{n,t} &= [Rain_{L,n,t}, Rain_{L,n,t} \times D_{n,t}, Rain_{L,n,t} \times Irrig_{n,t}, Rain_{L,n,t} \\ &\quad \times D_{n,t} \times Irrig_{n,t}, Rain_{R,n,t}, Rain_{R,n,t} \times D_{n,t}, Rain_{R,n,t} \\ &\quad \times Irrig_{n,t}, Rain_{R,n,t} \times D_{n,t} \times Irrig_{n,t}, Temp_{n,t}]. \end{aligned}$$

Here, $Y_{n,t}$ is a vector containing the following four endogenous variables: log agricultural yield, $Yield_{n,t}$; log nominal agricultural wages, $Wage_{n,t}$; log food prices, $Food_{n,t}$; and the change in the irrigation share, $\Delta Irrig_{n,t}$. In the baseline specification, the exogenous rainfall vector, $X_{n,t}$, consists of the following variables: purely local and regional rainfall shocks, $Rain_{r,n,t}$, where the subscript r refers to the spatial dimension of the shock (local L versus regional R); 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: $Rain_{r,n,t} \times D_{n,t}$.²⁷ This non-linear specification captures the different effects of negative and positive rainfall variations. In addition, all rainfall variables are interacted with the local irrigation share to capture the fact that a higher irrigation share reduces the importance of rainfall variation, that is, $Rain_{r,n,t} \times Irrig_{n,t}$ and $Rain_{r,n,t} \times D_{n,t} \times Irrig_{n,t}$. All rainfall effects (local versus regional, and positive versus negative) are thus estimated in one equation. The estimated coefficient vectors are denoted by α_i and β_i . In addition, $X_{n,t}$ contains the average temperature, $Temp_{n,t}$, in each district during the monsoon season as a control variable (taken from

²⁶The used criterion resembles a panel VAR adoption of the widely used maximum likelihood based model selection criteria of Akaike (1969).

²⁷In the presence of state-year fixed effects (see below), regional rainfall shocks capture all variations in distance-based regional rainfall variations that vary from state-level variations. Moreover, the present specification rules out that we measure a positive local rainfall shock in a year with a drought, only because the surrounding region's drought is even more severe. We thank an anonymous referee for prompting us to clarify this point.

the same source as rainfall data; Willmott and Matsuura, 2012).²⁸ Finally, γ_n and $\eta_{s,t}$ refer to the district and state–year fixed effects, respectively, and $e_{n,t}$ denotes the idiosyncratic error term.^{29,30}

4. Estimation results

In this section, we discuss the results based on impulse response functions.³¹ Section 4.1 presents our “baseline specification”, where we outline the responses of agricultural yield, wages, and food prices to four different types of variation in monsoon rainfall: negative local and regional rainfall variation, as well as positive local and regional rainfall variation, all at different levels of irrigation.³² Our estimation strategy ensures that a positive local (regional) rainfall shock represents a one-unit increase in overall standardized rainfall caused by a purely local (regional) rainfall shock when overall standardized rainfall is above its mean (and vice versa for negative shocks; see also footnote 27).

We then discuss the implications of our results. In Section 4.2.1, we evaluate the impact of state-level agricultural policy. In Section 4.2.2, we examine the role of barriers to trade and migration. In Section 4.2.3, we discuss the welfare implications of our findings among different demographic groups in rural India. Moreover, in Online Appendix A, we investigate 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.

²⁸Colmer (2018) argues that the effects of monsoon rainfall are likely overestimated when variations in temperature are not controlled for.

²⁹To account for the formation of 12 new Indian states between 1967 and 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.

³⁰The stability condition of the panel VAR is satisfied, as all eigenvalues lie inside the unit circle, that is, all moduli of the companion matrix are strictly less than one (Hamilton, 1994; Lütkepohl, 2005).

³¹Following the standard in the VAR literature, we analyse the VAR by inspecting its impulse response functions, which are a graphical representation of the elements of the model’s Wold MA representation (Lütkepohl, 2010) rather than by inspecting its estimated coefficients. As explained by Sims (1980), the estimated coefficients of such autoregressive systems are hard to interpret, given that there are complicated feedback effects within and across equations.

³²In addition, Figure 14 in the Online Appendix shows the impulse responses of the (differenced) level of irrigation to negative (local/regional) rainfall shocks. The results suggest that the area under irrigation expands less when the districts experiences a negative local/regional rainfall shock within the same year. All results are robust when we treat irrigation as exogenous variable in the panel VAR.

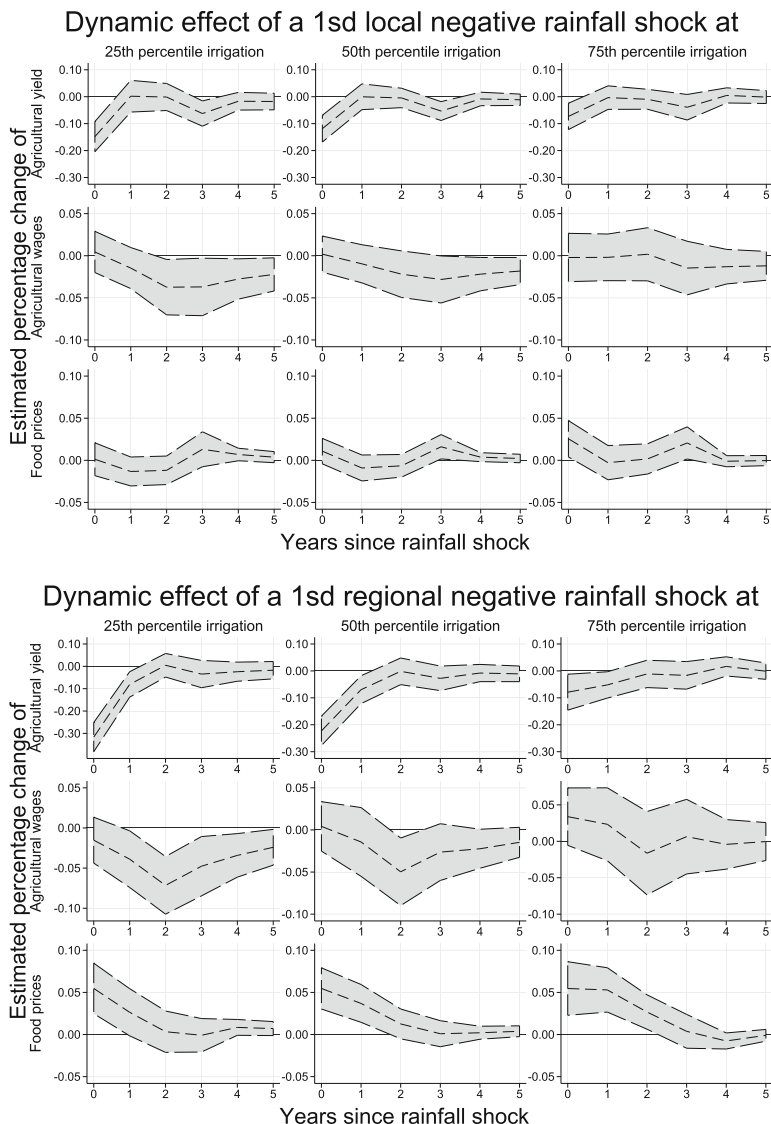
- (ii) We no longer distinguish between rainfall variation above and below the district mean (i.e., we implicitly assume that plant growth would be linearly increasing in water supply independent of the overall amount of rainfall).
- (iii) We exclude outlier districts from our sample (i.e., those districts with a rainfall standard deviation below the 5th and above the 95th percentile).
- (iv) We split the sample into subsamples covering the years 1967–1991 and 1981–2005 to examine the time stability of our results.
- (v) We investigate whether the shocks had different effects in the southern and eastern parts of India (where the monsoon arrives early) compared with the northern and western parts (where the monsoon arrives late).

4.1. Baseline specification

4.1.1. Negative local rainfall shock. The top panel of Figure 7 displays the effects of a one-unit decrease in overall standardized rainfall caused by a purely local rainfall shock when overall standardized rainfall is below its mean. We show the effects at the 25th, 50th, and 75th percentile of irrigation in our dataset (the average irrigation share at the respective percentile in our sample is 12, 26, and 47 percent). First, we observe that the adverse effects of negative local rainfall shocks on kharif yield are mitigated by irrigation: the size of the negative spike shrinks (in absolute terms) from about –15 percent at the 25 percent percentile to almost –12 percent at the median level, and to roughly –7 percent at the 75 percent percentile of irrigation, although it remains always statistically significant.³³ Moreover, the top panel of Figure 7 also shows that the decline in monsoon rainfall leads to a lagged, but persistent decline in the agricultural wage. At the first quartile of irrigation, the maximum impact of almost –4 percent occurs two years after the decline in monsoon rainfall. Moreover, the decline in the wage remains significant for up to five years after the rainfall shock. The delayed response likely relates to nominal wage rigidities in the Indian agricultural sector, as documented by Kaur (2019), who argues that downward real wage adjustments occur mainly through inflation and not through nominal wage cuts (see also Figure 6).³⁴

³³Note that we cluster standard errors at the district level. Clustering standard errors at the NSS region level gives very similar results. Standard errors clustered at the state level suffer from a small number of clusters (Özler, 2012).

³⁴Recall that both agricultural wages and food prices are measured in nominal terms, but as a percentage deviation from the model-implied mean. As we include state–year fixed effects, the model-implied mean captures general wage and/or price movements as well as all other developments at the state level (see Section 4.2.1).

Figure 7. Negative rainfall shock: responses to local rainfall variation (top panel) and to regional rainfall variation (bottom panel)

Notes: The top and bottom panels illustrate the impulse responses to a one-unit decrease in overall standardized kharif rainfall caused by a purely local/regional rainfall shock, respectively, when overall standardized kharif rainfall is below its mean. The gray area represents the 90 percent confidence interval based on standard errors clustered at the district level over a horizon of five years. The black dashed line within the gray area is the point estimate. The effects are presented for different levels of irrigation. The results are based on 2,952 observations at the selected lag-length.

Furthermore, we note that food prices remain essentially unchanged after a local reduction in monsoon rainfall.³⁵ This likely reflects the accommodating effects of intra-regional arbitrage trading, which avoid any substantial increase in food prices. This is in line with Allen and Atkin (2016) and Donaldson (2018), who find that improvements in infrastructure that facilitates trade have substantially reduced the exposure of agricultural prices to rainfall variation in India.

4.1.2. Negative regional rainfall shock. The bottom panel of Figure 7 presents the responses of agricultural yield, wages, and food prices to a one-unit decrease in overall standardized rainfall caused by a regional rainfall shock when overall standardized rainfall is below its mean. This corresponds to a general reduction of rainfall in the district itself and the surrounding area with a radius of 200 km. In addition, as documented in Section 2.2, we note that regional rainfall shocks are not randomly distributed across the monsoon season, but tend to arrive in the months most crucial for crop yield. Hence, we note that the effects on agricultural yield are now substantially larger, particularly at low levels of irrigation.³⁶ Again, the effects on agricultural yield are short-lived, having nearly completely disappeared in the following year and being no longer significant.

Compared with negative local rainfall shocks, we observe that the stronger response in agricultural yield translates into a roughly proportionally stronger response in agricultural wages. In particular, the maximum impact on wages is about 50 percent stronger, even though the effects dissipate somewhat faster about three years after the shock.³⁷ As in the case of local rainfall

³⁵This finding is consistent with the district-level result of Colmer (2018). We only note a small significant increase in districts with high levels of irrigation. Such districts might contribute disproportionately much to regional agricultural output, and hence to regional food price formation (albeit the amplitude remains small).

³⁶In addition, Table 3 examines whether the estimated stronger impact of negative regional rainfall shocks (compared with negative local rainfall shocks) might be caused by an insufficiently high resolution of the gridded rainfall data. In this case, measurement error at the district level would be higher than at the regional level, which potentially could contribute to a higher estimated impact on (more precisely measured) regional rainfall shocks. By contrast, when we split the full sample into “small districts” and “large districts”, we observe that the relative impact of regional (versus purely local) negative rainfall shocks is higher among “large districts” (which are less prone to measurement error). Our conclusions remain robust when we alternatively use rainfall data from the dataset of APHRODITE (2018), the database with the largest number of weather stations (see Yatagai et al. 2012 for documentation). The main reason why we do not use the APHRODITE (2018) dataset in the baseline specification is that its station network changes with time and season.

³⁷The 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.

Table 3. Same-year response of agricultural yield to negative local/regional rainfall shocks estimated using three different subsamples

	Baseline (1)	Small districts (2)	Large districts (3)
Panel A. Negative rainfall shocks at low irrigation			
Local Shock	-0.148*** (0.037)	-0.164*** (0.040)	-0.119** (0.067)
Regional Shock	-0.317*** (0.041)	-0.235*** (0.045)	-0.272*** (0.047)
Observations	2,952	1,503	1,449
Panel B. Negative rainfall shocks at medium irrigation			
Local Shock	-0.118*** (0.029)	-0.130*** (0.033)	-0.092*** (0.032)
Regional Shock	-0.223*** (0.034)	-0.175*** (0.038)	-0.149*** (0.037)
Observations	2,952	1,503	1,449
Panel C. Negative rainfall shocks at high irrigation			
Local Shock	-0.073** (0.029)	-0.078** (0.038)	-0.050 (0.046)
Regional Shock	-0.079* (0.042)	-0.083** (0.041)	0.037 (0.075)
Observations	2,952	1,503	1,449

Notes: The dependent variable is the same-year response of agricultural yield. Column 1 summarizes the estimated values for the baseline specification. Column 2 summarizes the estimated values for the subset of those “small” districts where the ratio between the district area and the corresponding region is less than 5 percent. Column 3 summarizes the estimated values for the subset of those “large” districts where the ratio between the district area and the corresponding region is between 5 and 15 percent. District-level clustered standard errors are reported in parentheses. ***, **, and * denote significance at the 1, 5, and 10 percent levels, respectively.

shocks, the impact on wages declines with the local level of irrigation and is no longer significant at the 75th percentile. Overall, the evidence suggests that agricultural wages are mainly determined by local circumstances (i.e., the drop in yield that depends on the local level of irrigation) rather than the spatial dimension (local/regional) of the rainfall shock. This indicates that, in the labour market, the arbitrage mechanism through (both intra- and supra-regional) migration is relatively weak.

Regarding food prices, we now observe an increase of close to 6 percent in the affected district across all levels of irrigation. We also note that the responses remain significant for up to three years.³⁸ There is only a very modest impact of irrigation mitigating the initial increase in food prices. Thus,

³⁸The observed positive correlation in food prices can be explained by storage activities (Wright, 2012), such as those of the Food Corporation of India (see also Section 4.2.1).

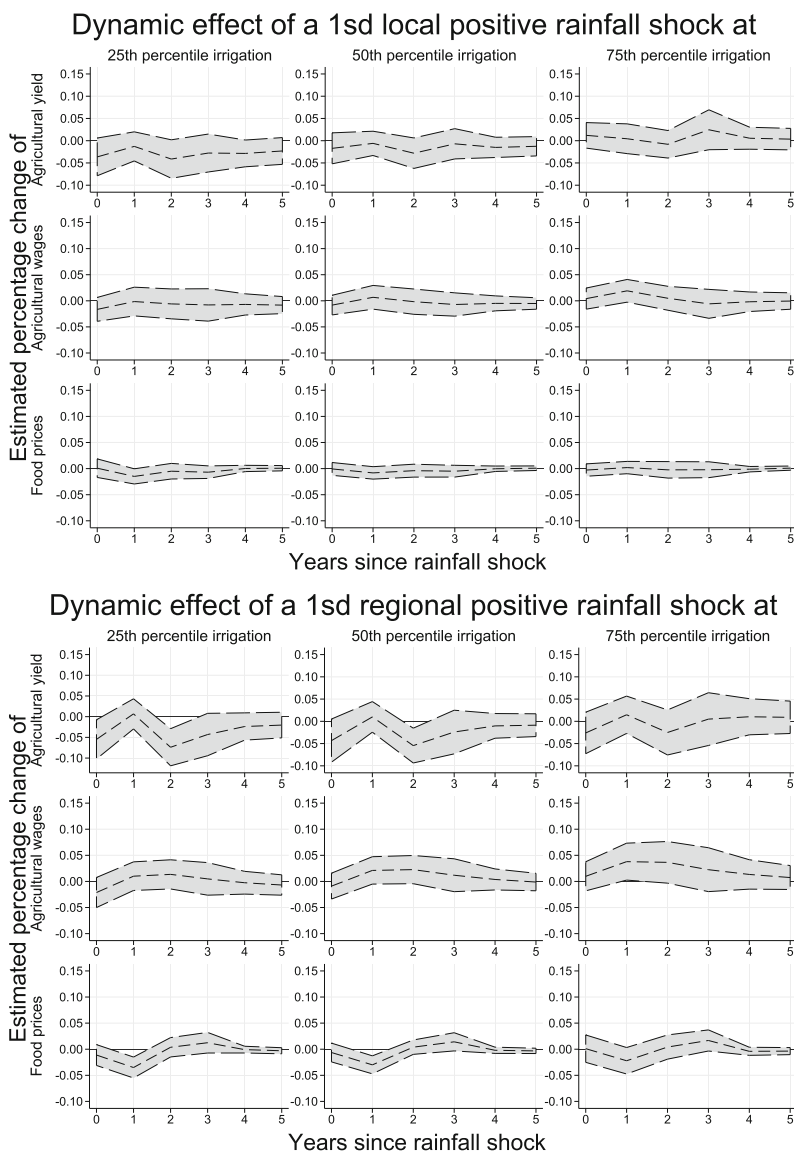
the almost uniform increase in food prices across the whole region does not relate directly to the decline of agricultural yield in the district. This implies that intra-regional arbitrage trading appears to be quite efficient at reducing the exposure to food price fluctuations due to local circumstances 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 (we elaborate on this question in Section 4.2.2).³⁹

4.1.3. Positive local rainfall shock. We now turn to the impact of positive rainfall shocks. The top panel of Figure 8 presents the responses following a one-unit increase in overall standardized rainfall caused by a purely local rainfall shock when overall standardized rainfall is above its mean. We observe that such a shock exerts no significant effects on either agricultural yield or on wages and food prices at any horizon. This implies that the effects of local rainfall variations are strongly asymmetric.⁴⁰ 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).

4.1.4. Positive regional rainfall shock. The bottom panel of Figure 8 presents the responses of agricultural yield, wages, and food prices to a one-unit increase in overall standardized rainfall caused by a regional rainfall shock when overall standardized rainfall is above its mean. Unlike in the case of positive local shocks, agricultural yield seems to decline initially, then to recover in the following year, but then to decline again before slowly returning back to normal. This pattern is apparent across all levels of irrigation, but the size of the confidence interval increases with the level of irrigation. This means that the response is no longer significant at the 75th percentile of irrigation. There is no significant effect on wages, even though the point estimate seems to suggest a small initial decline, followed by a small increase afterwards. Average (kharif) food prices show no significant response in the

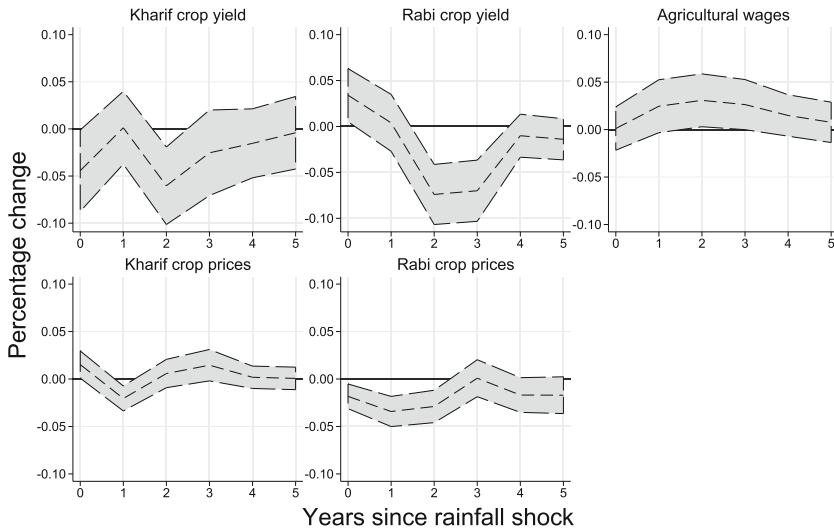
³⁹Note that the observed rise in food prices – a large part of the consumption basket in India – could be the driver of a faster adjustment in the agricultural labour market, as it allows for a quicker adjustment of real wages (see also Kaur, 2019).

⁴⁰This explains why our estimated elasticities to negative rainfall shocks are two to three times larger than the symmetric estimate of Jayachandran (2006). Other previous studies that have found non-linear effects of rainfall shocks in India include, for example, Lahiri and Roy (1985) and Gadgil and Gadgil (2006). These papers, however, have a different focus from ours in terms of selected variables and the geographical level of interest.

Figure 8. Positive rainfall shock: responses to local rainfall variation (top panel) and to regional rainfall variation (bottom panel)

Notes: The top and bottom panels illustrate the impulse responses to a one-unit increase in overall standardized kharif rainfall caused by a purely local/regional rainfall shock, respectively, when overall standardized kharif rainfall is above its mean. The gray area represents the 90 percent confidence interval based on standard errors clustered at the district level over a horizon of five years. The black dashed line within the gray area is the point estimate. The effects are presented for different levels of irrigation. The results are based on 2,952 observations at the selected lag-length.

Figure 9. Impact of a positive regional rainfall shock on kharif (summer) and rabi (winter) yield and prices



Notes: The figure illustrates the impulse responses of kharif crop yield and prices, rabi crop yield and prices, and agricultural wages to a one-unit increase in overall standardized kharif rainfall caused by a regional rainfall shock when overall standardized kharif rainfall is above its mean at the 25th percentile of irrigation. The number of observations at the selected lag-length is only 1,277 because of the high number of missing values for rabi crop yield and prices. For this reason, we adjust the confidence intervals to the 66 percent level (based on standard errors clustered at the district level and over a horizon of five years). The black dashed line within the gray area is the point estimate.

year of the shock, but then decline by -3.5 percent (-2.2 percent) at the 25th (75th) percentile of irrigation in the following year.

The delayed fall in (kharif) food prices likely reflects an increase in the production of rabi (winter) crops, which profit from additional water supply caused by above-average monsoon rainfall in the kharif season (e.g., through tank irrigation). This might reduce the harvest prices of substitutable kharif crops in the following year. Indeed, Figure 9 illustrates that the response of rabi crop yield (prices) to a positive regional rainfall shock in the kharif season is positive (negative).⁴¹ Thus, the (renewed) decline in kharif and rabi yield two

⁴¹To generate Figure 9, we additionally include agricultural yield and prices of typical rabi crops (i.e., wheat, barley, mustard, sesame, and peas) into the VAR. However, because of the limited availability of data for rabi crop yields and prices (the impulse responses in Figure 9 are estimated with less than half of the observations of those in the bottom panel of Figure 8), the presented results should only be seen as an illustration of the potential channel at work (see also, e.g., Kulkarni and Kurian, 2018). For this reason, the fact that the negative response of kharif yield in Figure 9 is insignificant does not establish a major concern.

years after the shock might be a result of reduced farming efforts of individuals with adaptive expectations in response to low crop prices in year one after the shock.⁴²

4.2. Discussion

4.2.1. The role of state-level agricultural policy. Agricultural policy in India is under the exclusive constitutional remit of state governments (see online appendix C of Atkin, 2013). Even though the central government of India also plays an important role in this matter (through, for example, the Food Corporation of India⁴³), for example, by stabilizing food prices through managing buffer stocks of food grains, distributing food grains through the Public Distribution System,⁴⁴ and regulating market prices for consumers, its responsibility is limited to allocating food grains to the state governments, whereas state governments are in charge of within-state allocation. Moreover, Atkin (2013) reports further that Indian state governments often impede internal trade through state tariffs and that, beyond state tariffs, additional district-level entry taxes exist in many Indian states (Das-Gupta, 2006). Moreover, state governments are also responsible for relief operations (Besley and Burgess, 2002). All this – as well as the poor state of the transportation infrastructure in India (Atkin, 2013) – might explain the observation of Waldman (2002) that starving individuals cannot afford to buy staple food, while at the same time stored grain rots in a neighbouring state.

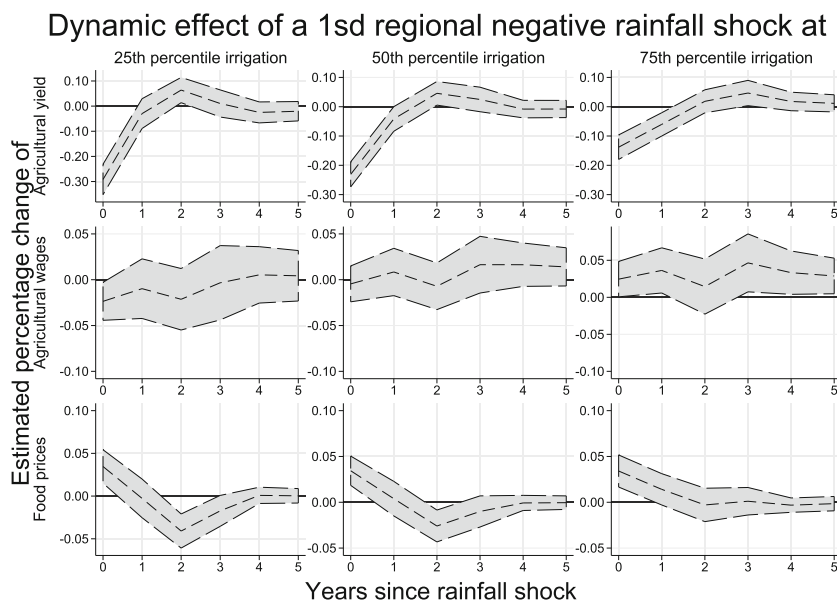
In our baseline specification, we account for changes in agricultural policy and state-level relief operations (as well as all other state-level developments, e.g., inflation, technological progress, improvements in infrastructure) by including state–year fixed effects. To assess whether these state–year fixed effects capture the impact of state-level policy, we replace them by (national-level) year fixed effects and we re-estimate the VAR. As can be seen from Figure 10, the main difference compared with our baseline specification is that the significantly negative response of wages to negative regional rainfall shocks turns insignificant (at the 25th and 50th percentile of irrigation), and the insignificant wage response at the 75th percentile of irrigation turns significantly positive. The impulse responses to all other shocks remain largely unchanged. This means that state–year fixed effects absorb a systematically positive contribution to the impulse response of wages in the aftermath of

⁴² An alternative explanation for this phenomenon is the phasing out of flood support for farmers that stabilized yield in the previous year, which could be because of declining media coverage on the provided flood support over time (see, e.g., Besley and Burgess, 2002).

⁴³ See <https://fci.gov.in/aboutUs.php?view=268>.

⁴⁴ See the website of the National Food Security Portal, Department of Food and Public Distribution, Government of India, https://nfsa.gov.in/portal/PDS_page.

Figure 10. Robustness: impact of a negative regional rainfall shock with national–year fixed effects



Notes: Instead of state–year fixed effects (as in the baseline specification), the PVAR underlying the current graph includes (national-level) year fixed effects. The gray area represents the 90 percent confidence interval based on standard errors clustered at the district level over a horizon of five years. The black dashed line within the gray area is the point estimate. The effects are presented for different levels of irrigation. The results are based on 2,952 observations at the selected lag-length.

negative regional rainfall shocks. Similarly, we observe that state–year fixed effects absorb a systematically positive contribution to the impulse response of agricultural yield (between the first and third year after the shock) and – as a mirror image thereof – a systematically negative contribution to the impulse response of food prices. This pattern likely reflects the expansionary impact of relief programmes, which lead to higher wage growth, higher agricultural yield, and lower food prices across the whole state; this implies that these relief programmes are not focused on the most affected districts with low levels of irrigation. We thus conclude that state–year fixed effects indeed help to isolate the impact of state-level policy interventions (e.g., relief programmes) from the impact of rainfall shocks.

4.2.2. Barriers to trade and migration. Our results from Section 4.1 indicate that, if regions are constructed using a distance-based measure, intra-regional arbitrage trading appears quite efficient at reducing the exposure

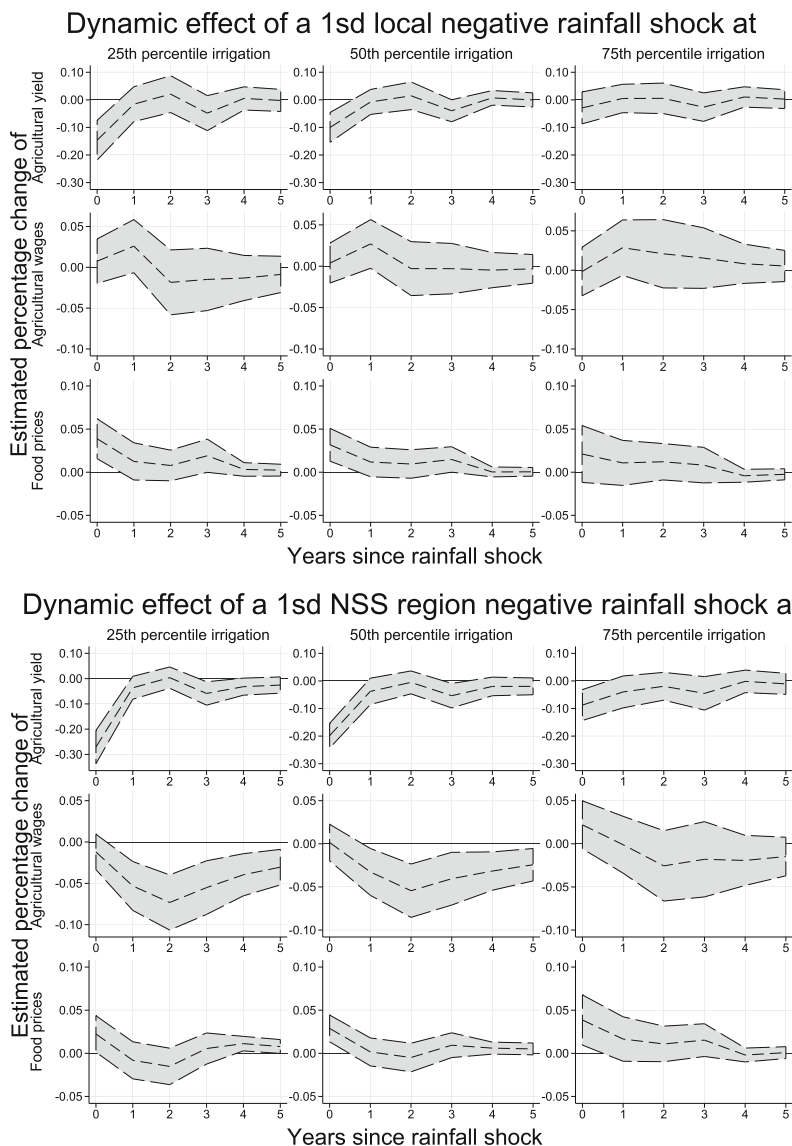
to food price fluctuations because of local circumstances in response to both local and regional rainfall shocks. However, the significant rise in food prices to negative regional shocks indicates that supra-regional agricultural trade networks in India are still incomplete. Moreover, in the labor market, the arbitrage mechanism through (both intra- and supra-regional) migration seems relatively weak. In the following, we instead construct regions based on the definition of the NSS. In contrast to the 200 km distance-based measure used in our baseline specification – which ensures that the district under consideration is centrally located within its region – the NSS (National Sample Survey Organisation, 2012a,b) defines regions as aggregates of districts within the *same* state “having similar geographical features, rural population densities and crop-pattern[s]”.⁴⁵

Figures 11 and 12 show that the key difference between the NSS and the distance-based baseline specification lies in the responses of agricultural wages and food prices to negative rainfall shocks. Compared with the baseline case, the impulse response of wages in the NSS specification becomes stronger in response to negative regional rainfall shocks, but weaker in response to negative local rainfall shocks. Regarding food prices, we observe almost the exact opposite: the impulse responses in the NSS specification become weaker in response to negative regional rainfall shocks, but stronger in response to negative local rainfall shocks.

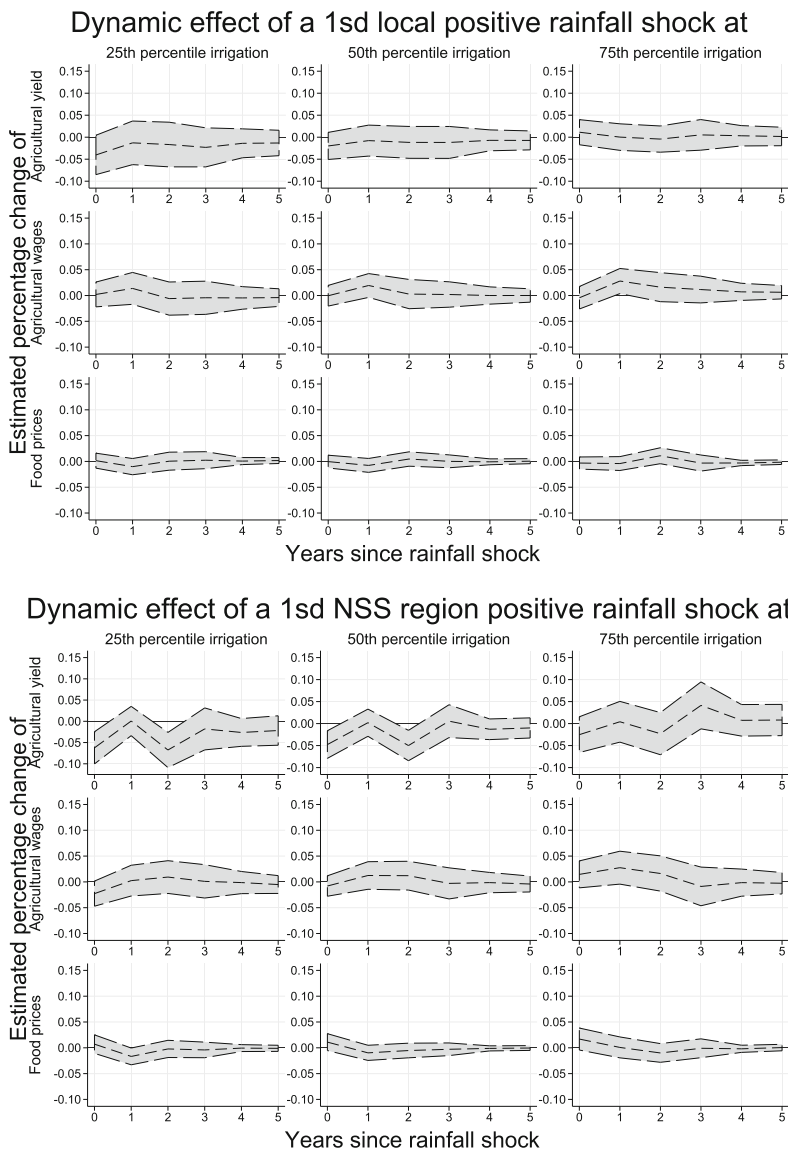
More specifically, these results indicate that internal migration across the whole NSS region is able to completely dampen the decline in local agricultural wages in response to a purely local negative rainfall shock. By contrast, internal migration less effectively mitigates the adverse effects of a negative rainfall shock affecting the whole NSS region – simply because all feasible internal migration destinations are also affected. The distance-based negative regional rainfall shock used in our benchmark specification thus partly captures a negative shock to areas that are relatively close, but no feasible internal migration destinations. In other words, affiliation to the same NSS region (rather than distance) seems to be a key determinant of internal migration.⁴⁶ Our finding is consistent with the results of Kone

⁴⁵Our results remain robust when we exclude those districts belonging to the set of 15 out of 36 Indian states and union territories (which account for about 7 percent of the land area) that consist of just one NSS region. In these 15 states/union territories, state-year fixed effects absorb all the variation in regional rainfall in the current specification.

⁴⁶This does not mean that NSS regions are well integrated migration units. Rather, this result implies that state borders are relatively more important for migration, while distance is relatively more important for trade in food products. Note, further, that the pattern found might be partly due to the fact that NSS borders often represent borders in terms of agro-climatic conditions. This means that the effects are not only caused by the administrative border as such, but also by the change in agro-climatic conditions. We thank an anonymous referee for pointing this out.

Figure 11. Impact of negative local/regional rainfall shocks based on administrative divisions

Notes: The regional shock is based on NSS regions (as defined in the 44th round, 1988) instead of a 200 km distance-based measure. The gray area represents the 90 percent confidence interval based on standard errors clustered at the district level over a horizon of five years. The black dashed line within the grey area is the point estimate. The effects are presented for different levels of irrigation. The results are based on 2,952 observations at the selected lag-length.

Figure 12. Impact of positive local/regional rainfall shocks based on administrative divisions

Notes: The regional shock is based on NSS regions (as defined in the 44th round, 1988) instead of a 200 km distance-based measure. The gray area represents the 90 percent confidence interval based on standard errors clustered at the district level over a horizon of five years. The black dashed line within the gray area is the point estimate. The effects are presented for different levels of irrigation. The results are based on 2,952 observations at the selected lag-length.

et al. (2018), who argue that state borders severely impede internal mobility in India.⁴⁷

Moreover, our results imply that intra-regional food trade – defined as trade within the district and the 200 km buffer zone – is able to completely dampen the rise in local food prices in response to purely local negative rainfall shocks. By contrast, intra-regional food trade – defined as trade within the NSS region – less effectively mitigates the adverse effects of a negative purely local rainfall shock. The negative NSS regional rainfall shock thus partly captures a negative shock to areas that belong to the same NSS region, but which are relatively remote. In other words, distance (rather than affiliation to the same NSS region and thus to the same state) seems to be the key determinant of trade in food products in India.⁴⁸ Our finding is consistent with the view that – despite large trade barriers between Indian states (see Section 4.2.1) – the poor state of the transportation infrastructure is still likely the biggest barrier to trade within India (see Atkin, 2013). During our sample period, cross-subsidization between freight and passenger services pushed up freight costs (National Transport Development Policy Committee, 2013), while road transport was being hindered by congested highways with poor surface quality (Singh and Kathuria, 2016). Moreover, even nowadays around one-third of all Indian villages are still not connected by all-season roads (World Bank, 2011).⁴⁹

4.2.3. Welfare effects across different demographic groups. Our main result is that (above all, negative regional) monsoon rainfall shocks exert adverse effects on the agricultural sector in India. The current section examines in which way different social groups in rural India are differently affected by these shocks. We thereby focus on the group of agricultural labourers – who typically make up a considerable share of the poorest individuals in rural areas (International Labour Organization, 1996) – and the group of cultivators.⁵⁰ To assess the associated welfare effects, we

⁴⁷ According to the authors, this finding can be attributed to the fact that states' own residents often have privileged access to subsidized goods, tertiary education (see also Ghose, 2021), and/or public sector employment. More precisely, Imbert and Papp (2020) argue that state borders per se are less relevant for seasonal migrants (compared with longer-term migrants). Our finding on the medium-run response of agricultural wages, however, is rather related to longer-term migration.

⁴⁸ Note further that, as NSS regions are subsets of states, NSS regional rainfall shocks might be more likely correlated with the corresponding policy response.

⁴⁹ See footnote 66 in the Online Appendix for further references on the impact of infrastructure.

⁵⁰ According to Census of India (2011), agricultural labourers receive a wage for their work and bear no risk in cultivation, whereas cultivators own or otherwise control land (e.g., through leasing) and earn the harvest.

perform the following two exercises. First, inspired by Jacoby (2016), we conduct a partial equilibrium analysis to estimate the dynamic impact of negative regional rainfall shocks on the two groups' purchasing power, based on the impulse responses estimated in Section 4.1.⁵¹ Second, we estimate the group-specific percentage change in nominal expenditures on basic staple foods (e.g., unprocessed vegetables) versus luxury goods (e.g., cigarettes and alcohol) following a negative regional rainfall shock (based on NSS data).

Partial equilibrium estimates. We now quantify the dynamic impact of negative regional rainfall shocks on purchasing power among agricultural labourers and cultivators. The exercise is of partial equilibrium nature, as we assume that: both groups spend a fixed share (i.e., 73 percent; see Ravallion 1998) of their income on food; expenditures on other consumption goods remain constant; there is no unemployment among agricultural labourers; and cultivators exclusively rely on their own labour input (which is fixed).⁵²

Panel A.2 of Table 4 shows that, because of downward nominal wage rigidities (Kaur, 2019), the income of agricultural labourers at median level of irrigation is relatively well protected in the short run.⁵³ in response to a negative rainfall shock, nominal wages remain essentially unchanged (see footnote 34). However, as food prices increase by more than 5 percent, the price index of their total consumption basket rises by almost 4 percent. Thus, their purchasing power falls by a similar amount (about 3 percent). Interestingly, their purchasing power remains at this level (close to 3 percent below the model-implied mean) on average over the next five years, implying that the effects of falling agricultural wages and normalizing food prices almost offset each other.⁵⁴ The purchasing power of cultivators at the median

⁵¹ A partial equilibrium approach appears most suitable given the data limitations when addressing this research question. For general equilibrium analyses, see, for example, Jacoby (2016) or Gallic and Vermandel (2020).

⁵² This also includes, for example, the fact that the area under cultivation remains constant.

⁵³ We focus on the effects at the median level of irrigation here. Table 4 displays the corresponding estimates at the 25th and 75th percentile of irrigation.

⁵⁴ More generally, we find that the adverse effects of negative regional rainfall shocks result from rising food prices and declining wages. Other studies, which do not focus on the effects conditional on rainfall shocks, find that agricultural wages and food prices tend to move in the same direction under different circumstances. 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

Table 4. Welfare effects among agricultural labourers and cultivators

	Level of irrigation		
	25th percentile	50th percentile	75th percentile
Panel A1. Effect of 1SD local rainfall shock on agricultural labourers			
Welfare change in year 0	0.4%	−0.6%	−2.0%
Welfare change in years 1–5	−2.7%	−2.1%	−1.1%
Panel A2. Effect of 1SD regional rainfall shock on agricultural labourers			
Welfare change in year 0	−5.3%	−3.4%	−0.5%
Welfare change in years 1–5	−4.9%	−3.3%	−0.9%
Panel B1. Effect of 1SD local rainfall shock on cultivators			
Welfare change in year 0	−14.8%	−11.6%	−6.7%
Welfare change in years 1–5	−1.9%	−1.5%	−0.9%
Panel B2. Effect of 1SD regional rainfall shock on cultivators			
Welfare change in year 0	−30.7%	−21.1%	4.1%
Welfare change in years 1–5	−2.8%	−2.1%	0.8%

Notes: The table shows the partial equilibrium effects of a one-unit decrease in overall standardized rainfall caused by a purely local/regional rainfall shock when overall standardized rainfall is below its mean on purchasing power of agricultural labourers and cultivators, respectively.

level of irrigation (see Panel B.2 of Table 4) drops in the short run by more than 20 percent, as the loss in agricultural yield cannot be compensated by the rise in food prices. Over the next five years, their purchasing power remains only about 2 percent below the model implied mean. Consequently, the average loss in purchasing power over a horizon of six years after a negative regional rainfall shock is somewhat larger among cultivators (about 5 percent) than among agricultural labourers (about 3 percent).

However, given that agricultural labourers are typically the poorest individuals in rural India (International Labour Organization, 1996), the smaller percentage loss in purchasing power might hit them harder. Moreover, it is quite plausible that the share of income spent on (staple) food among agricultural labourers (cultivators) is higher (lower) than the assumed value of 73 percent.⁵⁵ If agricultural labourers spend a higher income share on food, the adverse impact of higher food prices on their purchasing power is

of rural poverty. In contrast, Jacoby (2016), based on a general equilibrium framework, finds that rural households benefit from higher agricultural prices, as producer price run-ups translate into higher wages in the agricultural sector.

⁵⁵The value is taken from Ravallion (1998), who reports that the income share spent on overall food consumption remains relatively stable at about 73 percent for the first three income deciles, before eventually declining. However, Li (2021) argues that, with rising income, households also start to consume more expensive varieties in addition to staple food (but do not substitute away from staple food). In other words, the law of Engel (1857), according to which the poorest

aggravated,⁵⁶ while a lower income share spent on food among cultivators mitigates the adverse effects of higher food prices on their purchasing power (as their gains from selling excess harvest increase). Cultivators might additionally benefit from reduced wages if they do not rely exclusively on their own labour, but hire additional workers during the peak season.⁵⁷ However, reduced labour demand in the aftermath of negative regional rainfall shocks implies that agricultural labourers will receive the measured daily wage likely for a smaller number of days than usual. In conclusion, our partial equilibrium exercise likely underestimates (overestimates) the adverse impact on the purchasing power of agricultural labourers (cultivators).

Evidence from changes in consumption patterns. Next, we estimate the percentage change in nominal expenditures on basic staple foods (e.g., unprocessed vegetables) versus luxury goods (e.g., cigarettes and alcohol) among agricultural labourers and cultivators following a negative regional rainfall shock.⁵⁸ In contrast to the first exercise above, we now directly estimate the endogenous response in consumption expenditures, which is a function of both changes in income and changes in prices. For this purpose, we combine individual-level consumption data from the NSS (National Sample Survey Organisation, 2012a,b) with NSS region rainfall shocks (see Section 4.2.2 on the identification of these shocks).⁵⁹ Figure 13 shows that, on impact, agricultural labourers and cultivators reduce their consumption expenditures on staple foods to a similar extent; note that food

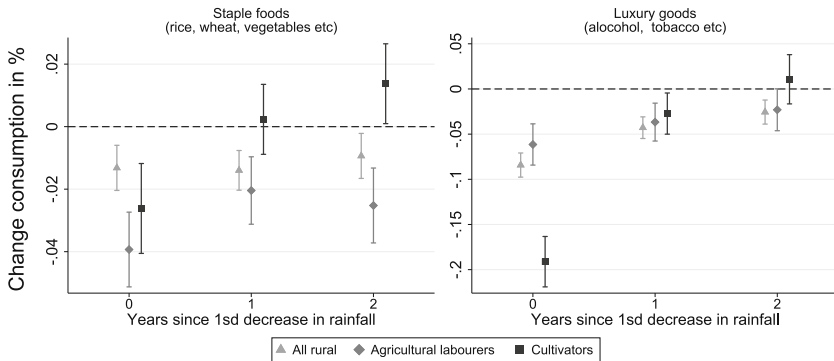
are over-proportionally affected by food price increases as they spend a bigger share of their income on food, rather applies to staple foods than to overall food consumption in contemporary India.

⁵⁶Note that the increase in food prices also affects individuals working outside the agricultural sector.

⁵⁷In this case, such large-scale cultivators are initially negatively affected by the drop in agricultural yield, but profit from lower labour costs and higher food prices in the following period. However, small-scale cultivators who lease rather than own the cultivated plot of land (so-called “share croppers”) likely suffer from the decline in the agricultural wage as lower wages reduce their outside option (see Chaudhuri and Maitra, 2000).

⁵⁸Based on the definition of Census of India (2011), we focus on those cultivators who own or control less than 3 ha of land – which includes more than 94 percent of all cultivators in the NSS (National Sample Survey Organisation, 2012a,b). Other individuals, who own or control more than 3 ha of land, likely do not belong to the rural poor in India.

⁵⁹NSS regions are the smallest geographical level in this dataset. We are therefore unable to distinguish between local and regional shocks, so that the estimated effects here reflect the responses to a pooled shock. Not having more detailed geographical data also makes it infeasible to distinguish the effects by irrigation levels. The consumption data are matched to agricultural years and cover the time period 1989–2006.

Figure 13. Drought impact on consumption patterns

Notes: Effect of a one-unit decrease in overall (local/regional) standardized kharif rainfall on individual consumption patterns aggregated at the NSS region level. The consumption data are matched to agricultural years and cover the time period 1989–2006. NSS region fixed effects and year fixed effects are included (individual fixed effects are not feasible, as the NSS sample represents repeated cross-sections). Results are presented for the sample of all individuals in rural areas as well as the two associated subgroups: agricultural labourers and cultivators. Numbers of observations: all rural = 247,346; agricultural labourers = 62,236; cultivators = 102,575. The 90 percent confidence intervals are based on robust standard errors.

prices increase (see Figure 11), which implies that real consumption falls even more strongly. Cultivators additionally need to reduce their expenditures on luxury goods enormously to avoid an even larger decline in consumption of staple foods. But only one year later, staple food expenditures of cultivators (as well as their luxury good expenditures) have converged back to normal, whereas staple food expenditures of agricultural labourers remain below normal for at least two more years after the shock.

The partial equilibrium exercise above has shown that both groups are severely hit by negative regional rainfall shocks – in percentage terms, cultivators are hit even slightly more than agricultural labourers – but the group-specific time profile of the impact is quite different (with all caveats in mind). The second exercise adds to this insight that, in contrast to agricultural labourers, cultivators seem to have more scope to smooth consumption of staple foods (e.g., by adjusting expenditures for luxury consumption goods or by depletion of savings). Consequently, the large drop in their agricultural income immediately following a negative regional rainfall shock causes only relative small and short-lived changes in their staple food expenditures. However, the persistent u-shaped decline in agricultural wages translates into below-normal levels of consumption expenditures on staple foods among agricultural labourers for several years. This indicates that this group consists of a large fraction of credit-constrained “hand-to-mouth” consumers, who are unable to insure against fluctuations in their income.

5. Conclusion

In this paper, we examine the dynamic effects of monsoon rainfall shocks on agricultural yield, wages, and food prices in India. In contrast to a static framework, our dynamic approach is able to capture the lasting effects that arise from sluggish price and wage responses in agricultural markets. In addition, we distinguish between positive and negative rainfall shocks and explicitly consider their spatial dimension (local/regional).

We find that the effects of monsoon rainfall shocks on agricultural yield in India are indeed highly asymmetric: depending on the local extent of irrigation, yield falls by up to 30 percent (15 percent) after a regional (local) drought, whereas positive rainfall shocks have only little effects. In particular, the estimated yield loss after negative monsoon rainfall shocks turns out to be two to three times higher than estimates based on conventional symmetric approaches. Moreover, our key novel finding is that the short-lived yield loss after a regional drought elicits a persistent decline (increase) in wages (food prices). Wages fall by up to 7 percent with the peak decline occurring two years after the drought and lasting up to five years. Food prices immediately rise by up to 5 percent, and remain at elevated levels for up to two years. The local extent of irrigation dampens the fall in agricultural wages after a regional drought, but not the rise in food prices.

In addition, we argue 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 (Kaur, 2019). However, in the medium run, their income deteriorates in real terms, owing to the persistent decline in wages and the persistent rise in food prices. This combination is particularly harmful to the rural poor in the face of incomplete credit markets (see Lanjouw and Shariff, 2004; de Janvry and Sadoulet, 2009), and thus might explain why famines (or, more generally, hunger) are generally considered to be caused by the unaffordability rather than the unavailability of food and that they can occur after agricultural output has already started to recover (Sen, 1981). Cultivators suffer from the short-term drop in agricultural yield, but might gain from the medium-term rise in prices for agricultural yield that is not used for own consumption. As a result, subsistence farmers who produce less for the market are more severely affected (see also footnote 5).

Several important policy conclusions can be drawn from our results. First, as the effects of (regional) droughts on real incomes are lasting, government support to affected individuals should be spread over several years. Second, we find that distance (rather than affiliation to the same NSS region and thus to the same state) seems to be the key determinant of food arbitrage trading. This result is consistent with the view that – despite large trade barriers

between Indian states – the poor state of the transportation infrastructure is still likely the biggest barrier to trade within India (Atkin, 2013). Trade in food products should therefore particularly benefit from investments in transportation infrastructure. Third, affiliation to the same NSS region (rather than distance) seems to be a key determinant of internal migration. This result is consistent with Kone et al. (2018), who argue that state borders severely impede internal mobility in India. Internal migration should thus particularly benefit from the reduction of legislative barriers to free movement of workers between Indian states. Fourth, our results imply that years of above-normal rainfall do not counterbalance the adverse effects in years of below-normal rainfall. Hence, the predicted increase in the variation of monsoon rainfall due to climate change (see, e.g., Dinar et al., 1998; Christensen et al., 2007; Kripalani et al., 2007) will also likely exert adverse effects (see also Guiteras, 2009),⁶⁰ because current excessive irrigation leads to dwindling levels of groundwater (Bansil, 2004). To avoid a backfall into rainfall dependence (Hertel, 2015), appropriate measures should be taken, such as investments in drip irrigation systems (Narayanamoorthy, 2004).

Supporting information

Additional supporting information can be found online in the supporting information section at the end of the article.

Online appendix Replication files

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⁶⁰ The projections of the climate models used by Kripalani et al. (2007) are based on the scenario that the atmospheric CO₂ 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.

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