Regional Crop Diversity and Weather Shocks in India

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Agriculture in both the developing and developed country context is highly sensitive to weather shocks. The intensity of these shocks is likely to increase under climate change, leading to an ongoing debate regarding the ability of farmers to insulate yields and income against accelerating environmental extremes. We study crop diversity as an avenue for increased resilience. Diversity in agricultural systems has been suggested in the agroecology and environmental economics literatures as a powerful means of on-farm insurance, both through physical and market-based channels. However, large-scale empirical evidence of its effectiveness is lacking, and crop diversity is largely absent from the empirical climate impacts literature. We examine the insurance benefits of crop diversity in the context of India at the height of the Green Revolution, a period of rapid change in agricultural diversification due to the increased penetration of a small set of high-yielding variety crops. Building on a basic empirical model from the climate impacts literature, we show that areas with higher crop diversity of planted area display measurably more drought resilience, both in terms of gross and net revenues. We decompose this aggregate result to show that diversification has implications for farmer welfare both through physical (yield) and market (price) channels.

Keywords: agriculture, climate change, crop diversity, weather shocks
JEL codes: Q10, Q15

I. Introduction

Food production, and hence farmer welfare, is highly vulnerable to weather shocks, particularly in the developing world, where few insurance mechanisms exist to buffer farmers against extreme weather events. The link between climatic conditions and agricultural yields has been extensively empirically documented for major crops in the North American context (Burke and Emerick 2016, Schlenker and Roberts 2009), and these findings have been replicated across the globe (Carleton and Hsiang 2016, Auffhammer and Schlenker 2014,

IPCC 2014). Indian agriculture is particularly susceptible to yield damage under adverse climate events, as production is heavily dependent on uncertain monsoon rainfall (Fishman 2016; Auffhammer, Ramanathan, and Vincent 2012), crop-damaging temperatures regularly depress yields (Carleton 2017; Welch et al. 2010; Auffhammer, Ramanathan, and Vincent 2006), and formal crop insurance is rare. By increasing the intensity of extreme climate conditions, global climate change is likely to exacerbate this vulnerability, raising important questions regarding whether and how the agricultural sector will adapt.

There are many adaptive behaviors and technologies that enable farmers to cope with weather-based uncertainty. These include investment in irrigation; development and use of new drought- and/or submergence-tolerant crop varieties (Dar et al. 2013); transfer of land and labor to nonagricultural sectors (Colmer 2016; Mendelsohn, Nordhaus, and Shaw 1994); shifting timing of planting or harvesting (Wright and Gardner 1995); and investment in formal crop insurance (Annan and Schlenker 2015). However, recent empirical work focusing on crop-specific avenues of adaptation has uncovered little to no evidence that farmers have successfully reduced yield sensitivity to accelerating climate change (Burke and Emerick 2016; Lobell et al. 2014; Schlenker, Roberts, and Lobell 2013; Schlenker and Roberts 2009). In contrast, a parallel body of work in agroecology has turned attention to across-crop solutions, suggesting that crop diversity has the potential to buffer both productivity (Bellora et al. 2017; Zimmerer 2010; Di Falco and Chavas 2008, 2009) and income (Baumgärtner and Quaas 2009, Di Falco and Perrings 2003) from adverse climate conditions. While researchers have proposed many mechanisms through which diversification of crop portfolios can enable adaptation, there is a dearth of large-scale empirical evidence of its effectiveness. Here, we use rich panel data from 270 districts across India during a period of rapid agricultural change to test whether shifts in macroscale (i.e., district-level) crop diversification have observable impacts on farmer income in times of extreme weather. Consistent with prior farm-level analyses (see, for example, Di Falco, Bezabih, and Yesuf 2010), we detect benefits of macroscale diversification for farmer revenues. In a novel test that isolates physical and market-based mechanisms, we show that diversification mitigates aggregate yield losses in times of drought, while simultaneously weakening drought-induced price shocks.

Our findings contribute to two distinct bodies of literature, which to date have remained independent. First, our results suggest that crop diversity is an effective, yet understudied, form of adaptation in the rapidly growing empirical literature on the agricultural impacts of climate change. This literature has demonstrated that while high temperatures and low rainfall are generally damaging to staple crops, there is substantial heterogeneity across crops in the weather–yield relationship. For example, rice in India is sensitive to rising nighttime temperatures (Welch et al. 2010; Auffhammer, Ramanathan, and Vincent 2006), while other major staple crops like maize, soy, and cotton suffer disproportionately under extreme daytime heat in

India and the United States (Burgess et al. 2014, Schlenker and Roberts 2009). Rice production throughout South and Southeast Asia has been found to be sensitive to the availability of rainfall during the monsoon season for nonirrigated systems, and to the availability of economically viable groundwater and surface water resources for irrigated systems (Auffhammer, Ramanathan, and Vincent 2012; 2006). Rainfall appears, however, much less important for crop production relative to temperature when researchers consider other crops and other regions of the world (Schlenker and Lobell 2010).

This heterogeneity suggests that diversification of crop planting, either at the farm level or at a more aggregate scale, may facilitate the resilience of total production and farm income to adverse climate conditions. However, this literature has focused on other means of adaptation. For example, the breeding of new crop varieties, which can more easily withstand climatic extremes, has received substantial attention. Dar et al. (2013) use a randomized field experiment in Orissa (now known as Odisha), India to show that a novel submergence-tolerant rice variety has substantial positive impacts on the mean and variance of rice yield. Maybe the most obvious avenue of adaptation to more uncertain rainfall regimes available to farmers is the installation of irrigation infrastructure, which has been observed throughout the major agricultural production areas globally. While demonstrably beneficial, irrigation as adaptation ceases to be feasible in the presence of insufficient groundwater or surface water (Fishman 2018). Other hypothesized forms of adaptation include shifting the planting calendar, switching crops, or exiting agriculture altogether. In this paper, we focus on the possibility that crop diversification may provide a means of adaptation that has thus far remained absent from climate change impacts research.

The second body of literature we contribute to is the active area of research on the benefits of biodiversity. Diversification is often cited as a means of reducing vulnerability to shocks, both within agriculture and in ecological systems more broadly (Bellora et al. 2017, Tilman et al. 2001, and Tilman and Downing 1994). Similarly, diversification as insurance is a well-accepted principle in finance and underlies modern portfolio theory. In the agricultural and agroecology literatures, crop diversification has been argued to enhance the ability of farmers and food production systems to respond to climatic variability by increasing the efficiency of water and nutrient use, enhancing species complementarities, and ensuring that species with heterogeneous climatic sensitivities exist jointly (Di Falco, Bezabih, and Yesuf 2010). However, much of the empirical agroecology literature has focused on a relatively narrow spatial scale and spectrum of crops (Gil et al. 2017), with findings often diverging (Di Falco, Bezabih, and Yesuf 2010). This is an active area of research with empirical studies covering much of the globe (Zimmerer 2010).

A number of economic studies have examined the benefits of crop diversification at various temporal and spatial scales. One literature builds on the

seminal paper by Rosenzweig and Binswanger (1993) looking at crop choice, farm level profitability, and weather risk. The majority of these papers have engaged in case studies of single farms or local production systems, which often specialize in a small number of crops. Gaudin et al. (2015) find significant yield benefits from cropping sequence diversification over a 31-year period of field trials in Ontario, Canada. They found that diversification led to yield increases of 7% for corn and 22% for soybeans. Di Falco and Chavas (2008) show that for cereals in Southern Italy, higher biodiversity is consistent with better production outcomes during negative rainfall events. Di Falco, Bezabih, and Yesuf (2010) demonstrate similar findings for a panel of farms in Ethiopia. They show that higher crop diversity leads to better production outcomes during bad rainfall events, suggesting that diversity is consistent with higher resilience. These papers and the references cited therein comprise a flourishing literature, which appears to suggest empirical evidence of the benefits to resilience from higher crop diversification. The advent of massive new data sets of high resolution land cover imagery will certainly revolutionize this literature as one will be able to look at both temporal and spatial changes in crop diversity locally and globally.

In this paper, we seek to make a modest contribution to the literature with two innovations. First, we test whether we can detect evidence of increased resilience at a macroscale of diversification, in contrast to the field- and farm-level analyses that dominate previous work.[1] Second, we separately identify two key pathways linking diversity and climate resilience. Nearly all studies focus on the production benefits of diversification, citing or testing for particular mechanisms like the species complementarities discussed above. However, the manner in which these production effects manifest as changes in farmer welfare depend critically on endogenous price responses. Baumgärtner and Quaas (2009) describe a model in which formal market insurance and "natural insurance" realized through diversification of a crop portfolio are substitutes. In this conceptual framework, farmers adopt diversification in the presence of uncertain climate conditions when formal market insurance is absent or costly, as is the case in much of India. However, the advantages of such natural insurance depend on the extent to which local prices move in tandem with diversity-moderated yield shocks. To our knowledge, we provide the first empirical evidence that diversification influences both physical production and local price levels.

Our study is set in the context of India during the onset of the Green Revolution, which dramatically transformed Indian agriculture. Following decades of frequent famines, the early 1960s saw the rollout of high-yielding varieties (HYVs) of cereals (particularly wheat), increased rollout of irrigation infrastructure,

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[1]See Zimmerer (2010) for a discussion of the role of geographic scale in agroecological studies of crop diversity.

and more frequent use of pesticides and fertilizers as well as machinery. On the institutional side, this period saw land reforms and the related consolidation of landholdings as well as the broad availability of credit access for farmers. As a consequence, diversity generally fell through increased adoption of HYVs and other agricultural inputs that facilitated a transition toward more monoculture-based production systems. This transition was particularly stark in North India. We use these spatial and temporal differences as a source of variation in crop diversity at the district level, where the average Indian district is slightly larger than the average county in the United States.

We use annual weather, agricultural price, production, and cost data measured in each district and each year to test whether district-level crop diversity is correlated with higher gross or net farm revenues per hectare in years of drought. Our estimation results suggest that in drought years, districts with higher levels of agricultural diversity experience higher gross and net revenues per hectare. These aggregate results can arise not only through physical benefits of diversification on crop yields, but also through changes in local prices to the extent that markets are not fully integrated across space. In what we believe is a novel decomposition of the income effect, we test whether the impacts of diversity during drought periods affect crop yields and agricultural prices simultaneously. We find evidence that revenues are affected both through physical impacts on yields and through a farm gate price mechanism. Our estimation results show that these impacts are robust across space and to the inclusion of controls for unobservables in the form of district and year fixed effects as well as regional trends. The remainder of the paper is organized as follows. Section II briefly describes the data employed in our estimation. Section III describes the empirical model. Section IV presents and discusses the results. Section V concludes with some suggestions for further research.

II. Data

The agricultural data at the district level used in this paper come from the India Agriculture and Climate Data Set. We use the original data set created by Sanghi, Kumar, and McKinsey (1998), which covers the period 1956–1987. These data contain area planted, output, and farm gate prices for major crops (pearl millet, sorghum, maize, rice, and wheat) as well as minor crops (barley, cotton, groundnut, chickpea, jute, potato, finger millet, pigeon pea, rapeseed and mustard, sesame, soy, sugarcane, sunflower, tobacco, and a collective category called "other pulses"). Area planted is reported in thousands of hectares, output is reported in thousands of tons.

As Zimmerer (2010) discusses, the study of crop diversity and how it is measured depends greatly on the spatial scale of analysis. Studies of single crops often extend down to the level of different types of strawberry plants. We do not

have data at this scale. Also, indicators of diversity often take into account different spatial arrangements of planting patterns for individual crops—the "surrounding landscape," which is thought to play an important ecological role. We do not have a field-level database, which would allow us to generate an indicator to take these important dimensions into account. Finally, there is the diversity in crop rotation studied by Gaudin et al. (2015), which looks at temporal measures of diversity. We only observe annual data and hence cannot investigate the order of planting and harvest. Given these limitations, we create a simple yet widely used indicator of concentration, the Herfindahl–Hirschman Index (HHI), based on area planted to different crops in a given year and district. While this measure is relatively coarse when compared with field-level analyses, it enables us to investigate whether the microscale findings from the existing literature scale to an aggregate level. Moreover, this macroscale indicator enables us to investigate the market response to diversification, as measured by local prices.

Our HHI for district i and year t is defined as follows:

$$HHI_{it} = \sum_{j=1}^{J} s_{ijt}^2 \tag{1}$$

where $s_{ijt} = \frac{a_{ijt}}{\sum_{j=1}^{J} a_{ijt}}$ is the share of total planted area in district i dedicated to crop j in year t. J is the total number of crops, which in our data set comprises the 20 major and minor crops listed above.[2]

Our weather data are monthly averages and were aggregated up from weather stations to districts and weighted by the inverse squared distance from district centroid to each station. We define the kharif (monsoon crop) growing season as June through September and rabi (winter crop) as November and December (Carleton 2017, Guiteras 2009). We use cumulative growing season rainfall and average growing season temperature as explanatory climatic variables. We create an indicator for extremely low levels of rainfall, using the lowest tercile of kharif season rainfall for each district as the cutoff value, following Auffhammer, Ramanathan, and Vincent (2012), and Burgess et al. (2014).

Our agricultural price index is based on Burgess et al. (2014), which is a simple index with time-invariant crop weights. Each crop j in each district i is weighted by the average percentage of total crop revenue derived from crop j. That is, the weight for crop j in district i is calculated by

$$w_{ji} = \frac{1}{T} \sum_{t=1}^{T} \frac{P_{jit} Q_{jit}}{\sum_{j=1}^{J} P_{jit} Q_{jit}} \tag{2}$$

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[2]We used the HHI over the Shannon Index since our data contain many crop and year combinations with zero area planted.

The price index for each district *i* in year *t* is calculated as

$$P_{it} = \sum_{j=1}^{J} P_{jit} w_{ji} \tag{3}$$

where P_{jit} is the crop-specific price (in rupees/quintal) as reported in the raw data (Sanghi, Kumar, and McKinsey 1998).

We first conduct our analysis for all districts with available data across India. To test for spatial heterogeneity based on the location of emergence of the Green Revolution, we split India into North (Gujarat, Haryana, Punjab, Rajasthan, and Uttar Pradesh) and South (Andhra Pradesh, Bihar, Karnataka, Madhya Pradesh, Maharashtra, Odisha, Tamil Nadu, and West Bengal). We run versions of our models allowing the effect of crop diversity during drought years to vary between the North and the South. Table 1 provides the complete summary statistics for our sample of districts and also breaks them out by geographic region. The summary statistics indicate that the northern districts are significantly drier during the kharif season on average and in terms of extremes. This is not surprising since the southern states are part of the monsoon belt, where much of the rain-fed rice agriculture is based. The northern districts are also warmer during the kharif season with an average monthly temperature that is almost 1.5 degrees Celsius higher than the southern states.

To create indicators of farmer income, we construct measures of both gross and net revenues per hectare of planted area. Gross revenues are simply the sum of all production returns for each crop, where prices and quantities are taken directly from the India Agriculture and Climate Data Set. Net revenues subtract estimated labor and fertilizer costs from gross revenues. However, these input costs are heavily interpolated and results for net revenues should therefore be interpreted with caution. The statistics on net revenue per hectare in Table 1 indicate similar net and gross revenues per hectare in the North and the South. Yields in terms of tons per hectare are not statistically different in the North than in the South. There is no statistical difference in area planted per district between the two groupings of states. If we consider the share of irrigated crops across the two groupings, 24% of area planted was irrigated in the North across the entire sample, while the same average is only 18% for the South. Further, the farm gate price index is slightly higher in the South, although the difference is not statistically significant.

Figure 1 displays our main variable of interest, the HHI of crop diversification across time, separately for the North and South. We see a trend consistent with the onset of the Green Revolution in the mid-1960s. The North experienced a steady increase in HHI over time. Two things stand out. First, there is the drastic increase in the index over time in the North, which is indicative of a move toward more monoculture. This relationship is not clear in the South, where the HHI stays somewhat constant on average. Figure 2 displays the HHI plotted against the share

Table 1. **Summary Statistics—All India, North India, and South India**

Variable	All India					North		South	
	Obs.	Mean	Std. Dev.	Min	Max	Mean	Std. Dev.	Mean	Std. Dev.
Precip JJAS	8,401	0.86	0.51	0.01	5.43	0.71	0.36	0.96	0.57
Precip ND	8,401	0.04	0.07	0.00	0.76	0.01	0.02	0.05	0.09
Temp JJAS	8,401	28.53	2.07	21.10	34.52	29.92	1.50	27.62	1.88
Temp ND	8,401	20.64	2.41	10.57	27.66	19.28	2.22	21.55	2.07
Total Revenue/ha (thousands)	8,401	1.07	0.95	0.00	29.24	1.02	0.88	1.09	1.00
Net Revenue/ha (thousands)	8,401	0.19	1.13	−44.07	19.56	0.20	0.68	0.19	1.35
Yield (tons/ha)	8,401	0.86	0.46	0.00	15.08	0.89	0.45	0.84	0.46
Area (thousand ha)	8,401	535.35	293.89	3.10	2,177.41	540.69	275.03	531.82	305.72
Share irrigated	8,401	0.20	0.16	0.00	0.92	0.24	0.15	0.18	0.16
Price Index	8,401	134.75	85.74	6.36	832.35	129.47	84.31	138.25	86.51
HYVs Share of Area Planted	8,401	0.11	0.12	0.00	0.58	0.12	0.13	0.10	0.12
HHI Diversification Index	8,401	0.37	0.21	0.11	1.00	0.30	0.16	0.42	0.23

ha = hectare; HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops); HYVs = high-yielding varieties; JJAS = June, July, August, and September; ND = November and December.

Notes: "Precip" refers to cumulative seasonal rainfall measured in meters. "Temp" refers to average seasonal temperature measured in degrees Celsius.

Source: Authors' own calculation from data constructed by Sanghi, Apurva, K. S. Kavi Kumar, and James W. McKinsey Jr. 1998. *India Agriculture and Climate Data Set.* Washington, DC: World Bank.

Figure 1. **Time Series of Crop Diversity Index**

(a) North   (b) South
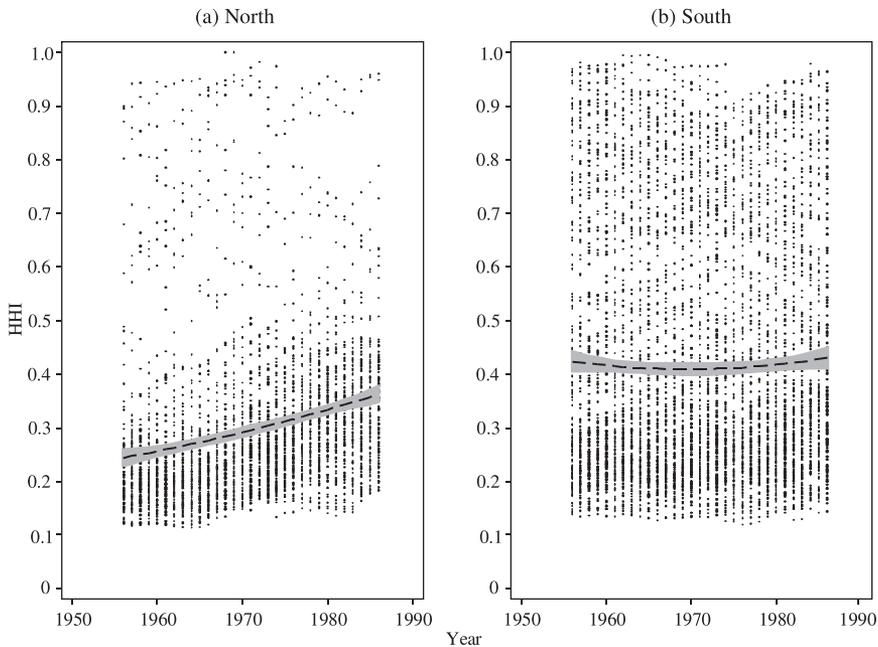
HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops).
Notes: North India includes Gujarat, Haryana, Punjab, Rajasthan, and Uttar Pradesh. South India includes Andhra Pradesh, Bihar, Karnataka, Madhya Pradesh, Maharashtra, Odisha, Tamil Nadu, and West Bengal.
Source: Authors' own calculation from data constructed by Sanghi, Apurva, K. S. Kavi Kumar, and James W. McKinsey Jr. 1998. *India Agriculture and Climate Data Set.* Washington, DC: World Bank.

of HYVs in terms of area planted. The HYVs rollout in the North correlates strongly with decreased diversity, as is evidenced by the increase in the HHI from 0.20 to 0.34 for the districts in Punjab, Uttar Pradesh, and Haryana. This means that while Green Revolution technologies were taken up at relatively similar rates across India, only in the North did this imply lower crop diversity. Second, there is significantly more variability in the South in the HHI than in the North.

We now use these data to examine whether more diverse cropping systems are more resilient to rainfall shocks in the form of a drought.

III. Empirical Model

Auffhammer, Ramanathan, and Vincent (2012) previously examined the role of rainfall extremes on rice yields throughout India using aggregate state-level data. They show that higher incidence of drought and an increase in more intense rainfall events, conditional on total monsoon rains, lead to measurable depressed yields for

Figure 2. **Crop Diversity Index and Share of Area Planted to HYVs**
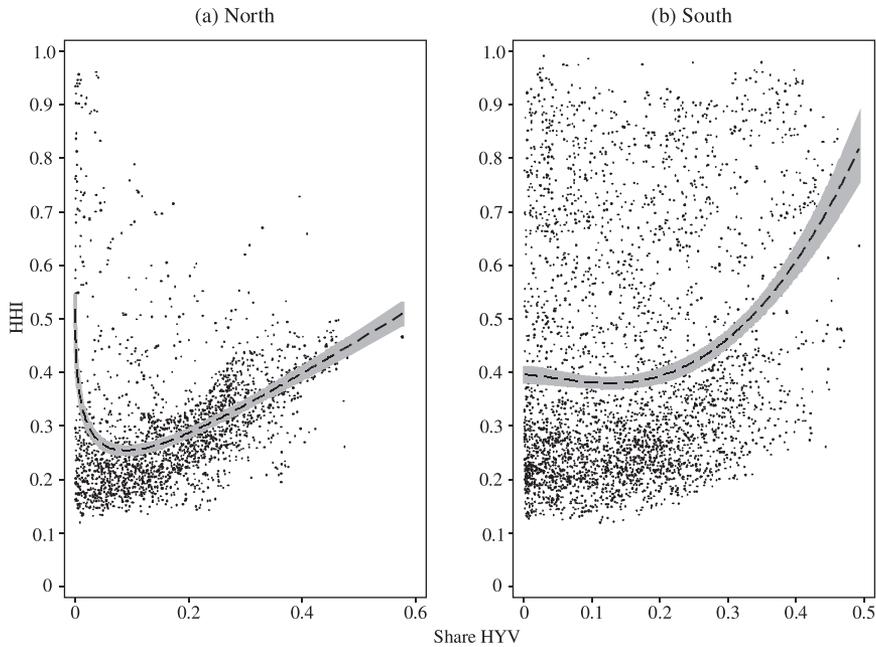
HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops), HYVs = high-yielding varieties.

Notes: North India includes Gujarat, Haryana, Punjab, Rajasthan, and Uttar Pradesh. South India includes Andhra Pradesh, Bihar, Karnataka, Madhya Pradesh, Maharashtra, Odisha, Tamil Nadu, and West Bengal.

Source: Authors' own calculation from data constructed by Sanghi, Apurva, K. S. Kavi Kumar, and James W. McKinsey Jr. 1998. *India Agriculture and Climate Data Set.* Washington, DC: World Bank.

rain-fed rice. We adopt a similar econometric specification as a starting point, which is given by

$$y_{it} = \alpha_i + \theta_t + \beta_1 HHI_{it-1} + \beta_2 HHI_{it-1} * drought_{it} + \beta_3 drought_{it}$$
$$+ \beta_4 Temp_{it} + \beta_5 Precip_{it} + \varepsilon_{it} \tag{4}$$

where y_{it} is one of our four outcome variables (gross revenue per hectare, net revenue per hectare, yield per hectare, and price index) in district i and year t; α_i, and θ_t are district and year fixed effects, respectively;[3] $drought_{it}$ is a dummy variable indicating a low rainfall year; $Temp_{it}$ is a vector of seasonal (kharif, rabi) average temperature; and $Precip_{it}$ is a vector of seasonal (kharif, rabi) cumulative rainfall. The additive error term ε_{it} is assumed to be serially correlated across time, yet independent across districts.

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[3]For robustness, we show additional results including region-specific time trends in place of year fixed effects.

The variable y_{it} will be one of four different variables. In a first set of regressions we will use gross revenues (in rupees) per area planted, which is simply the sum of revenues from all crops grown in a district-year. In a second set of regressions, we will use net revenues, which account for costs of major inputs to production. In a third set of regressions we will use yield, which is simply total output (in tons) aggregated across crops and measured per unit of area planted. This measure of course does not directly link to farmer income, as weight in tons and the economic value of crops are not necessarily positively correlated. In a final set of regressions, we will put our price index based on equation (3) as the dependent variable. We will run all regressions for all of India and then examine whether there is evidence of spatial heterogeneity between the North and South, and between more and less heavily irrigated areas.

The variable *drought* is a dummy equal to 1 when cumulative kharif season rainfall is in the first tercile of rainfall for district *i* in year *t*, based on the distribution of that district's rainfall over the entire sample time period. $Temp_{it}$ comprises two variables, kharif and rabi average monthly temperature, and is an important control, given the negative impacts of heat on yields in India (Burgess et al. 2014; Guiteras 2009; Auffhammer, Ramanathan, Vincent 2006).

The variables of interest in these regressions are HHI_{it-1} and $HHI_{it-1} * drought_{it}$. The coefficient β_1 will measure the relationship between lower crop diversity and each dependent variable directly and hence is of interest in itself. The coefficient β_2 will measure the relationship between lower crop diversity during drought years and each dependent variable, and is the main coefficient of interest. If higher diversity makes districts more resilient to droughts, we would expect a negative coefficient on this interaction term for the net and gross revenue and yield regressions.[4]

In our regressions we include HHI and its interaction with the drought variable as lagged by one period, which makes them econometrically predetermined in the time series sense. We estimate all equations with district and year fixed effects to control for temporal effects within each district and time-invariant state characteristics, respectively. Identification hence comes from within-district variation, conditional on the year fixed effects and other observable controls. The coefficients on all weather variables—*Temp*, *Precip*, and *drought*—can be interpreted causally as these within-location realizations are plausibly exogenous (Carleton and Hsiang 2016). However, given significant temporal dependence in the diversity measure, our use of a lagged independent variable is imperfect and β_2 may be affected by unobserved heterogeneity. In the absence of a readily available instrument, we see this approach as the best one can do to assuage endogeneity concerns. We interpret all our findings regarding the HHI interaction

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[4]Recall that a higher HHI indicates higher concentration in area planted, and hence lower diversity.

Table 2. **Ordinary Least Squares Estimation Results—All India**

	Gross Revenue	Gross Revenue	Net Revenue	Net Revenue	Yield	Yield
HHI	−0.059	−0.255	−1.212**	−2.371***	0.107	−0.417
	(0.831)	(1.057)	(0.516)	(0.698)	(0.452)	(0.546)
HHI × Drought	−0.211***	−0.160**	−0.565*	−0.565*	−0.077***	−0.074***
	(0.072)	(0.070)	(0.323)	(0.306)	(0.027)	(0.025)
Drought	0.027	0.003	0.155	0.126	0.003	−0.010
	(0.026)	(0.027)	(0.105)	(0.095)	(0.012)	(0.011)
Temp JJAS	−0.006	0.170***	0.055*	−0.019	−0.030**	0.003
	(0.024)	(0.015)	(0.034)	(0.021)	(0.012)	(0.006)
Precip JJAS	0.011	0.092**	0.021	−0.034	0.016	0.054***
	(0.050)	(0.042)	(0.055)	(0.061)	(0.024)	(0.017)
Temp ND	−0.018	−0.062***	−0.072***	−0.066***	−0.007	−0.019***
	(0.012)	(0.006)	(0.026)	(0.008)	(0.005)	(0.003)
Precip ND	0.413	0.019	−0.714	−0.602	−0.014	−0.041
	(0.349)	(0.318)	(1.140)	(0.889)	(0.168)	(0.141)
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No	Yes	No
Region Trends	No	Yes	No	Yes	No	Yes
Observations	8,401	8,401	8,401	8,401	8,401	8,401
R-squared	0.711	0.683	0.388	0.373	0.697	0.699

FEs = fixed effects; HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops); JJAS = June, July, August, and September; ND = November and December.
Notes: "Precip" refers to cumulative seasonal rainfall. "Temp" refers to average seasonal temperature. "Drought" refers to a binary indicator defined as equal to 1 when cumulative JJAS season rainfall is in the first tercile of the district-specific rainfall distribution. Gross and net revenues are measured in thousands of rupees per hectare; yield is measured in tons per hectare. Standard errors are clustered by administrative district and are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.
Source: Authors' calculations.

as correlational. All of our estimates cluster standard errors by district. The next section discusses the results from estimating different versions of equation (4).

IV. Estimation Results

Table 2 displays the estimation results for our main specification. The first two columns show the estimation results from estimating equation (4) using gross revenues per hectare as the dependent variable for all of India, controlling for year fixed effects (column 1) versus region-specific trends (column 2). All models control for district fixed effects. We find a negative yet statistically insignificant parameter estimate on the diversity index, suggesting that there is no correlation between crop diversity and gross revenues per hectare, conditional on the included observables and fixed effects or trends. The interaction of the HHI indicator and the drought dummy is significantly different from zero and negative, which is consistent with more diverse districts having higher gross revenues per hectare during drought

years. Its point estimate suggests that a one sample standard deviation higher HHI during a drought year would result in 4.4% less gross revenue per hectare for that district. If we use net revenues, the sign of the interaction term is similar, yet the point estimate and associated uncertainty are larger. A one standard deviation increase in the HHI has a roughly two and a half times larger negative effect during drought years, which of course works through gross revenues as well as labor and input expenditures. The latter are not well measured in the data set, which leads us to suggest that the gross revenue regressions provide a more reliable estimate of impacts. The last two columns in the table conduct a simple yield regression and the results carry the same sign and statistical significance. In average years, diversity has no distinguishable impact on crop yields, but in times of drought, districts with lower diversity suffer substantially lower yields. The standardized magnitude of the effect on yields is smaller than that for gross revenues, suggesting that a one standard deviation increase in the HHI is consistent with a 1.9% decrease in yields.

Table 3 examines whether there is heterogeneity in the estimated effects in terms of location of the district or how heavily irrigated the district is. To test whether the northern districts are more or less resilient than the southern districts, we include an interaction term of our variable of interest with a dummy for the northern states. The first three columns of the table show these results. The point estimates on the interaction term of interest between the drought dummy and the HHI are almost identical to those in Table 2. The interaction term with the North India dummy is not statistically different from zero, suggesting that there is little evidence of heterogeneity in terms of a North–South divide, despite substantial differences in the rollout of Green Revolution technologies.

We then generate a dummy variable called "Irrig," which equals 1 if more than 30% of a district's area is irrigated. This represents the top quartile of the districts in terms of the share of area irrigated. The interaction is included in the last three columns of Table 3. In the gross revenue and yield regression, the point estimate on the interaction term is opposite in sign to the now slightly larger point estimates on the regular interaction, which suggests that the resilience benefit from higher diversification appears to be concentrated in districts with lower shares of irrigated area.

The effect of crop diversification on revenue resilience in light of drought depends both on physical responses of crops to the diversity of the local portfolio, as well as on the degree to which diversity can moderate the influence of weather shocks on local prices. For example, if markets throughout India were perfectly integrated, local prices would fail to reflect local climatic conditions and diversification would matter for farming households only through its effects on crop yields. However, if local prices were fully determined by local production, negative supply shocks in drought years would be accompanied by price increases, helping to buffer income effects through a natural market mechanism. To test whether and

Table 3. **Ordinary Least Squares Estimation Results—All India Heterogeneity Effects**

	Gross Revenue	Net Revenue	Yield	Gross Revenue	Net Revenue	Yield
HHI	−0.069	−1.206**	0.098	−0.097	−1.176**	0.090
	(0.831)	(0.533)	(0.452)	(0.832)	(0.492)	(0.452)
HHI × Drought	−0.213***	−0.564*	−0.079***	−0.293***	−0.486**	−0.114***
	(0.073)	(0.327)	(0.028)	(0.069)	(0.224)	(0.025)
HHI × Drought × North	0.061	−0.040	0.055			
	(0.116)	(0.274)	(0.041)			
HHI × Drought × Irrig				0.303***	−0.293	0.136***
				(0.100)	(0.418)	(0.041)
Drought	0.021	0.159*	−0.003	0.023	0.159	0.001
	(0.032)	(0.093)	(0.013)	(0.027)	(0.109)	(0.012)
Temp JJAS	−0.007	0.056	−0.032***	−0.007	0.056*	−0.031***
	(0.024)	(0.036)	(0.012)	(0.024)	(0.033)	(0.012)
Precip JJAS	0.010	0.022	0.014	0.003	0.029	0.012
	(0.050)	(0.056)	(0.024)	(0.050)	(0.055)	(0.024)
Temp ND	−0.018	−0.072***	−0.007	−0.015	−0.075***	−0.006
	(0.012)	(0.026)	(0.005)	(0.012)	(0.029)	(0.005)
Precip ND	0.415	−0.716	−0.011	0.424	−0.725	−0.009
	(0.349)	(1.132)	(0.168)	(0.348)	(1.144)	(0.170)
District FEs	Yes	Yes	Yes	Yes	Yes	Yes
Year FEs	Yes	Yes	Yes	Yes	Yes	Yes
Observations	8,401	8,401	8,401	8,401	8,401	8,401
R-squared	0.711	0.388	0.698	0.712	0.389	0.698

FEs = fixed effects; HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops); JJAS = June, July, August, and September; ND = November and December.
Notes: "Precip" refers to cumulative seasonal rainfall. "Temp" refers to average seasonal temperature. "Drought" refers to a binary indicator defined as equal to 1 when cumulative JJAS season rainfall is in the first tercile of the district-specific rainfall distribution. "North" refers to a binary indicator defined as equal to 1 when the district is within Gujarat, Haryana, Punjab, Rajasthan, or Uttar Pradesh. "Irrig" refers to a binary indicator defined as equal to 1 when more than 30% of a district's planted area is irrigated. Gross and net revenues are measured in thousands of rupees per hectare; yield is measured in tons per hectare. Standard errors are clustered by administrative district and are reported in parentheses. ***$p < 0.01$, **$p < 0.05$, and *$p < 0.1$.
Source: Authors' calculations.

how local prices are influenced by crop diversity in addition to the yield effects documented above, we regress our price index on the same set of covariates we use in the previous two tables. The first two columns in Table 4 use the pooled all-India sample. Columns 3 and 4 look at whether the price response varies across space. These regressions suggest a statistically significant correlation between the price index and the interaction of the diversification index with the drought indicator. However, this effect is quantitatively small: a one standard deviation increase in the HHI during a drought year is consistent with a roughly 1.5% higher price index. If we look at the interaction in the last two columns, this effect is much larger in North India, where the effect is 4%. The interaction between the drought variable and the diversification index suggests that in drought years, less diverse districts see slightly higher farm gate prices, alongside lower yields.

Table 4. **Ordinary Least Squares Estimation Results—Price Index**

	Price Index	Price Index	Price Index	Price Index
HHI	−53.558[***]	16.505	−55.131[***]	15.207
	(12.050)	(15.445)	(11.951)	(15.355)
HHI × Drought	10.101[**]	12.103[***]	9.801[**]	11.637[***]
	(4.235)	(4.046)	(4.141)	(3.998)
HHI × Drought × North			9.940[*]	14.588[**]
			(5.598)	(5.945)
Drought	−1.135	−1.496	−2.176	−3.003
	(2.002)	(2.007)	(2.127)	(2.144)
Temp JJAS	6.788[***]	19.910[***]	6.583[***]	19.511[***]
	(1.729)	(1.300)	(1.730)	(1.306)
Precip JJAS	1.959	7.306[**]	1.701	6.936[*]
	(3.232)	(3.592)	(3.235)	(3.590)
Temp ND	−0.779	−2.801[***]	−0.807	−2.811[***]
	(0.983)	(0.591)	(0.987)	(0.591)
Precip ND	−5.210	−33.327[***]	−4.779	−32.741[***]
	(12.539)	(10.959)	(12.525)	(10.928)
District FEs	Yes	Yes	Yes	Yes
Year FEs	Yes	No	Yes	No
Region Trends	No	Yes	No	Yes
Observations	8,401	8,401	8,401	8,401
R-squared	0.816	0.782	0.816	0.782

FEs = fixed effects; HHI = Herfindahl–Hirschman Index (calculated over area planted to 20 different crops); JJAS = June, July, August, and September; ND = November and December.
Notes: "Precip" refers to cumulative seasonal rainfall. "Temp" refers to average seasonal temperature. "Drought" refers to a binary indicator defined as equal to 1 when cumulative JJAS season rainfall is in the first tercile of the district-specific rainfall distribution. "North" refers to a binary indicator defined as equal to 1 when the district is within Gujarat, Haryana, Punjab, Rajasthan, or Uttar Pradesh. Total and net revenues are measured in thousands of rupees per hectare; yield is measured in tons per hectare. Standard errors are clustered by administrative district and are reported in parentheses. $^{***}p < 0.01$, $^{**}p < 0.05$, and $^{*}p < 0.1$.
Source: Authors' calculations.

V. Conclusions

Our empirical results suggest that Indian districts with a more diverse crop mix are indeed more resilient in the presence of droughts. We show economically small, yet statistically significant, effects on gross and net revenues. We document that these impacts materialize both through a physical effect on yields, as well as through changes in local prices. We see no heterogeneity between North India and South India in the revenue and yield regressions, but do detect a higher price response in the North compared to the South. We show some suggestive evidence that these benefits seem to be negated in heavily irrigated districts, where irrigation serves as a backstop for bad rainfall outcomes, as long as irrigation water is available from groundwater or surface sources. These findings contribute both to the literature seeking to understand possible adaptation pathways for agriculture under anthropogenic climate change, as well as to the body of research quantifying the benefits of increased diversification in agricultural and agroecological systems.

There are several caveats to our analysis. This observational study suggests correlations only, as we have to rely on the fact that our lagged diversification index is predetermined. A proper, and hugely costly, experimental design would randomly encourage farmers in different districts to increase the diversity of crops grown. This is clearly not feasible in the short run at this scale. A meta-analysis of the studies listed in Zimmerer (2010) might serve as an interesting next step for future research.

Many outstanding questions regarding the resiliency benefits of crop diversity go beyond the resources available for this study. They include a more careful examination of which type of heterogeneity is responsible for the largest gains in resilience. For example, are the aggregate gains from diversification due to heterogeneity in minor crops? Or, are the observed benefits only realized when minor and major crops together provide a diversified portfolio? We hope that increased availability of satellite imagery over time will allow us to more closely examine these questions for large-scale panel data. Closer collaboration between ecologists, agricultural economists, and data scientists might provide a fruitful path forward to disentangle the mechanisms behind these effects and better understand the associated economic benefits and costs.

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