At What Price?
Price Supports, Agricultural Productivity, and Misallocation

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Abstract

Agricultural price support policies are a popular way to alleviate the risk inherent in volatile prices, but, at the same time, may distort input allocation responses to agricultural productivity shocks across multiple sectors. This could reduce productivity in the agricultural sector in developing countries. I empirically test for misallocation in the Indian agricultural setting, with national price supports for rice and wheat. I first motivate the setting using a two-sector, two-factor general equilibrium model and derive comparative statics. I then use annual variation in the level of the national price supports for rice and wheat relative to market prices, together with exogenous changes in district-level agricultural productivity through weather shocks, in a differences-in-differences framework. I derive causal effects of the price supports on production patterns, labor allocation, wages, and output across sectors. I find that rice area cultivated, rice area as a share of total area planted, rice yields, and rice production all increase, suggesting an increase in input intensity (inputs per unit area) dedicated to both staple crops. Wheat shows a similar increase in input intensity. The key input response is a reallocation of contract labor from the non-agricultural sector during peak cultivation periods, which results in an increase in wages in equilibrium in the non-agricultural sector (especially in response to price supports for the labor-intensive crop, rice, of 23%). The reallocation of labor reduces agricultural productivity by 82% of a standard deviation, and simultaneously reduces gross output in non-agricultural firms by 2.6% of a standard deviation. I also find that rice- and wheat-producing households do not smooth consumption more effectively in response to productivity shocks in the presence of price supports.

Keywords: Price Supports, India, Agricultural Production, Inputs, Labor Allocation
JEL codes: J43, O12, O13, Q12, Q18

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1 Introduction

Agricultural productivity in developing countries is low[1], and the productivity gap across sectors is large[2]. Simultaneously, farmers are unable to completely smooth consumption in response to shocks[3]. In response, a number of countries have adopted price support policies for various crops, in an effort to help farmers hedge against these risks[4]. However, prices on the open market, absent other frictions, are a mechanism for allocating inputs efficiently within the agricultural sector, and across sectors. We lack causal estimates of the effect of price supports on 1. distortions to farmers' production and input decisions, 2. total factor productivity in the agricultural sector, and 3. wages and output in the non-agricultural sector.

In this paper, I empirically study the extent to which price supports contribute to low agricultural productivity, and the productivity gap across sectors. I focus on the Public Distribution System in India, one of the largest such programs in the world. I look at the implications of price supports for farmers' crop choices, agricultural input selections, and decisions about non-agricultural work. I also study the resulting equilibrium effect on wages and output in both sectors. To do this, I interact weather-driven variation across space and time in local agricultural productivity (and therefore in local market prices) with changes in the level of the national-level price support in a differences-in-differences framework. I build a two-sector model of allocation decisions for capital and labor across the agricultural and non-agricultural sectors, with and without price supports. The model describes the various channels through which prices mediate farmers' responses to agricultural productivity shocks and provides useful comparative statics.

There are two main reasons that India's price support policies are an effective context for testing the implications of such policies for farmers' decision-making. First, national price supports for rice and wheat[5] are announced in June at the beginning of each agricultural season, and are therefore known to farmers before planting. Second, there is variation between 1997 and 2012 - my time period of interest - in the extent to which the policy has kept up with local market prices, which provides important variation in the salience of the program to farmers[6,7].

First, I show that the support price is high in some years and low in others, relative to the entire predicted distribution of market prices for rice and wheat. This provides variation across the years in the probability that the price support will bind for a given district.

[1] Kuznets (1971), Gollin et al. (2002), Caselli (2005), Restuccia et al. (2008), Chanda & Dalgaard (2008), Vollrath (2009), Lagakos & Waugh (2010), Gollin et al. (2011), Herrendorf & Schoellman (2011)

[2] Gollin, Lagakos, and Waugh (2011) estimate this to be 3.63 in the case of India

[3] Morduch 1995, Dercon 2002, Santangelo 2016

[4] Bangladesh, Brazil, Myanmar, Egypt, Indonesia, Mali, Pakistan, and Zambia, among other countries (World Bank Agricultural Distortions Database). The FAO finds that 27% of the 81 developing countries surveyed had price supports in place as of Jan 1, 2008.

[5] The Indian price supports are significant to farmers only for two staple crops, rice and wheat, in separate seasons. I discuss the implementation of these price supports in detail in section 2.

[6] There are two, more minor, benefits to studying the Indian price support policy: First, this is a long-standing policy, with a single policy arm. The Indian government has provided price supports for staple crops since the 1970s, which reduces concerns that farmers are wary of the government reversing course on the price supports it announces at the time of planting, or that farmers need time to learn about the logistics of the policy. Second, the policy has shown little variation in the way that it is administered - eligibility criteria, key crops targeted, etc. - in the period I study.

[7] There are also advantages of assessing the impact of price supports in a developing country. Agricultural policies in developed countries (particularly in the US and across the EU), are often more nuanced than the Indian policy, and do not therefore provide an appropriate context for studying the direct influence of price supports on agriculture. They often involve a combination of income supports and quotas, do not apply in a blanket way to all farmers, and do not directly address price volatility. I also expect the responses of farmers to be very different in a context in which land-holdings tend to be smaller and more heavily focused on staple crops, farming is more labor-intensive, and farmers have less access to instruments such as futures contracts to address price volatility.

Second, each district's level of early-season rainfall serves as an exogenous, pre-planting, district-level shock to agricultural productivity. I verify that these local productivity shocks significantly affect the wholesale prices for rice and wheat that are eventually realized in the district; non-negative rainfall shocks (what I refer to in the paper as "good rain") lead to lower prices at harvest. So, it is clear that local market prices adjust in response to productivity shocks. There are two different distortions that price supports create in this environment; first, they allow farmers to sell output at a constant price (and not at the falling local market price) in response to positive productivity shocks, and second, in the case that they are set above a district's local market price, they provide an income shock that increases the marginal return to investing in agriculture relative to the non-agricultural sector. I consider both distortions together in this paper.

Importantly, both the level of the price support and the local early-season productivity shock are known to farmers before they make planting and input decisions.

To capture how responses to productivity shocks differ with and without price supports, I estimate the differential effect of "good rain", and therefore higher productivity, on various production metrics in years in which support prices are high relative to years in which they are low. Having determined that there is a positive effect on agricultural output and yield, I consider the effect of the policy on various inputs to agriculture, including labor, to identify the channels through which the production measures are affected. Third, I consider the effect of this input reallocation across sectors on productivity in the agricultural sector, and output in the non-agricultural sector. Finally, I study the differential effect of agricultural productivity shocks on household income for staple-producing households in high- and low- price support years as a measure of the income support provided by the policy.

There are four key results. First, the paper provides causal empirical evidence that price supports result in increased input intensity (amounts of input used per unit area) in the agricultural sector. I find that the Indian price support policy increases area, area share, yield, and production of rice. The increase in area and area share of rice suggest that farmers respond to the financial incentives of the price support by increasing the intensity of rice production. The increases in raw yield of rice further suggest increases in input intensity per hectare, beyond a simple reallocation of land towards a more input-intensive crop. I find a similar increase in yields and input intensity for wheat[8]. These production gains are restricted to districts that are relatively suitable for rice and wheat respectively.

The second key result is that these increases in area (for rice), yield and production (for both crops) coincide with a reallocation of labor from the non-agricultural to the agricultural sector, particularly during peak cultivation periods (when the marginal returns to investing labor in production are highest). I confirm that this reallocation is driven by contracted (short-term) employees rather than permanent employees of non-agricultural firms. For a sense of magnitude, among agricultural households, this is a decrease in days engaged in non-agricultural labor of 35% for rice and 19% for wheat. I find no effect of price supports on labor supply on the extensive margin, or other inputs. I turn to the model for the intuition behind these results. According to the two-sector, two-factor general equilibrium model I build, there are two competing effects of higher productivity in the agricultural sector on labor use in the *absence* of price supports: first, that a lower relative price for agricultural goods (and the resulting income effect) leads to increased demand in the non-agricultural sector and a reallocation of inputs away from agriculture[9], and second, that higher

[8]There is no change in total area cultivated in the *Rabi* season- the main wheat-producing season - in response to higher price supports, nor in the area or area share dedicated to wheat. However, even as area remains constant, production and yield both see significant increases, suggesting a similar increase in input intensity as for rice.

[9]Similar reasoning has been developed in models by Murphy et al. 1989, Kongsamut et al. 2001, and Gollin et al. 2002.

relative productivity in agriculture puts upward pressure on wages and results in a reallocation of labor into agriculture. Price supports partly negate the first channel, leaving the second to dominate.

Taken together, the results show crowding out effects in the non-agricultural sector as a result of the distortion in agricultural prices. I confirm this by analyzing output in the formal manufacturing sector, and find that it falls by 8.5% in years in which price supports are high, in response to positive productivity shocks in agriculture. The paper therefore provides initial evidence on the ability of price support policies to slow the growth of the (more productive) non-agricultural sector in a transition economy[10]. In addition, the loss in manufacturing output amounts to 0.83% of India's GDP, which, when taken into account, effectively doubles the implicit cost of these price supports.

More broadly, these results can be extended to intuit the effect of increasing agricultural market integration (and therefore a single price across districts, in the extreme case) in developing economies on the sectoral allocation of inputs. In a world without market integration, increased productivity in the agricultural sector through a local rainfall shock reduces local market prices and strengthens the reallocation of inputs away from agriculture. With market integration, prices are inelastic to local productivity shocks, and farmers behave as they would when exposed to agricultural price supports.

Next, I ask whether the reallocation of labor into the non-agricultural sector can, in fact, reduce agricultural productivity. In accordance with the literature, I construct a Tornqvist-Theil index of agricultural TFP, aggregating across crops and across various inputs. I find a 0.82 standard deviation decrease in this measure of agricultural productivity in response to a positive agricultural productivity shock when price supports are high relative to when they are low. This is driven by the increase in labor use in the agricultural sector. This result, together with the crowding-out effects in the non-agricultural sector, suggests that not only do price supports policies hinder growth in the non-agricultural sector - they also have a negative impact on productivity *within* agriculture.

Finally, this paper also examines whether a price-support policy can provide income support in an environment in which prices run counter to productivity shocks and serve as an automatic stabilizer for income. Agricultural price support policies pay out when prices are low but production is high. In the case of India's price support program, I find that price supports do not improve consumption-smoothing in response to productivity shocks.

This paper contributes to the literature on the link between agricultural productivity and the growth of the non-agricultural sector (Bustos et al. 2012, Hornbeck & Keskin 2014, and many others). Studies based in India conclude that the factor bias of the productivity shock drives the direction of the effect on the non-agricultural sector[11]. Specifically, I examine the short-run effect of Hicks-neutral agricultural productivity shocks, driven by rainfall[12], on labor allocation and output in the non-agricultural sector, and then ask how these are affected by agricultural price supports. Studies on the effects of such rainfall shocks on the non-agricultural sector have identified two channels through which the sectors are related: (1) wages

[10]The literature suggests that non-farm growth is key to increasing rural wages and reducing rates of poverty. In rural India, in particular, growth in the non-agricultural sector has been rapid, and has contributed more than double to rural growth than the use of agricultural technologies such as high-yielding varieties of seeds (Foster & Rosenzweig 2003).

[11]Studies on the Green Revolution in India have found a negative relationship (over the long term) between labor-augmenting technological progress and output and labor allocation to the manufacturing sector in India (Foster & Rosenzweig 2004, Moscona 2017), while studies on short-term responses to rainfall shocks, assumed to be Hicks-neutral, have found the opposite (Emerick 2016, Santangelo 2016).

[12]There is an expansive related literature on the effect of rainfall shocks on agricultural inputs, including labor (Jayachandran 2006, Kaur 2017, and others), which suggests that rain is important for agricultural productivity.

and (2) relative prices and demand (Lee 2014, Emerick 2016, Santangelo 2016). These studies find that the latter channel is stronger in the case of India, leading to labor movements out of agriculture in periods of good rainfall, which I confirm in this paper. In addition, as a contribution to this literature, this study is the first to separately identify the contribution of the producer price channel to this effect. I find that, in the presence of worker mobility[13], price supports simultaneously reduce wages for agricultural workers and increase the fraction of workers in agriculture, and reduce output and employment in the non-farm sector.

A second literature supports the idea that risk may have a significant impact on agricultural production. We know, for instance, that missing markets for insurance in many developing countries affect crop choice. Farmers continue to face shocks to output and prices, but lack access to financial instruments that could hedge against risk. Small farmers do not typically enter into futures contracts, and index insurance (that hedges against weather shocks) remains rare (Cole et al. 2009, Binswanger-Mkhize 2011)[14]. Their decisions about what to plant are therefore distorted by risk. There are two types of empirical work within this literature. First, farmers without access to insurance products tend to use production decisions to hedge against risk, even at the cost of expected income (Rosenzweig & Stark 1989, Fafchamps 1992, Morduch 1995, Dercon 1998, 2002, Dercon & Christiaensen 2011, Falco et al. 2014). Second, farmers diversify into more risky crops and invest more in inputs following the provision of various types of insurance (Karlan et al. 2014, Gehrke 2014, Cole et al. 2017), and large-scale government transfer programs (e.g. workfare programs, social transfers) (Bhargava 2015, Gehrke 2017)[15].

I contribute to this literature by examining the production and the labor allocation responses to a specific policy-driven reduction in *price* volatility in the agricultural sector. There are two ways in which this paper differs from the insurance and agricultural production literature. First, there is little existing evidence of the price support policy's effectiveness as an income support - this is because, unlike insurance, it pays out at times when lower prices might be offset by higher output. Second, experiments involving insurance tend to occur on a smaller scale. This price support policy covers all farmers in India, and my findings show that the aggregate effect (that cannot be studied through experiments) on labor allocation across sectors and non-agricultural outupt is large.

A third strand of literature deals with the direct effects of price volatility on farmers. Allen & Atkin (2016) find, for example, find that farmers shift towards less risky crops in the presence of increased income volatility (and decreased price volatility) in response to reduced trade costs[16]. This paper adds to this literature by using clear policy variation to assess the effect of price supports that are meant solely to alleviate price volatility, but which are themselves focused on staple (less risky) crops. This is in contrast to examining the impact of reducing price volatility through trade, in which there is wide-ranging impact on outcomes ranging from market access to input availability, rather than only on price volatility in a single sector.

A fourth strand of literature looks specifically at the effects of price supports in the agricultural sector, but does so by simulating an artificial price support as part of a structural model (Jonasson et al. 2014, Mariano & Giescke 2014). This paper adds to this literature by estimating the concrete effect of a particular price support policy, rather than making the various requisite assumptions for a structural estimation.

[13]Prior work finds that, in the Indian context, there is a great deal of short-term movement of labor between sectors (Imbert & Papp 2015, Colmer 2017, and others). Workers are often engaged on a daily or weekly basis, and, even among those who are engaged primarily in agriculture, devote some time to non-agricultural activities.

[14]In the 2012-2013 agricultural cycle, 95% of rice- and wheat-producing households did not insure their staple crop.

[15]In addition, these government policies have been shown to have labor market effects in similar contexts (Ardington et al. 2009, Basu et al. 2009, Azam 2012, Berg et al. 2013, Santangelo 2016), in particular by increasing non-agricultural wage rates.

[16]In the form of expansions in the highway network

The paper proceeds as follows: Section 2 provides background on the agricultural sector and institutional details about the timing of the policy that drive my empirical strategy. Section 3 provides a two-sector model of input allocation and derives useful comparative statics. Section 4 presents my empirical strategy and validates that early-season rainfall affects realized market prices in the harvest period, which implies that it influences farmers' expectations of prices. Section 5 details how I aggregate information on prices, crops produced, area for each crop, production, yield, farmers' expenditure at harvest, and rainfall into a district-level panel for the time period 1997-2012. Section 6 presents results and a discussion of the broader implications of my findings. Section 7 provides a numeric estimate of the effects of the price support on agricultural productivity. Section 8 presents various robustness checks to validate my results, and discusses potential confounds. Section 9 concludes.

2 Background and Context

Price supports are especially relevant to farmers in the context of the Indian agricultural sector, because farmers tend to be small, price takers in their local wholesale market, and lack access to insurance to hedge against the price risks that the policy protects against. I describe the agricultural sector in subsection 2.1.

I rely on two key factors about minimum support prices in my empirical strategy. First, they are announced before planting and known to the farmer without uncertainty. Second, there is an element of randomness in the level of the price support from the perspective of the farmer, because they are set at the national level. Price supports are applicable only to two staple crops, rice and wheat, and I focus specifically on these crops in my analyses. I go on to describe the process of setting the minimum support price (MSP) and its implications in 2.2. I tie the implementation of the program into the farmer's decision-making timeline in 2.3.

2.1 Agriculture in India

Indian agriculture is characterized by small-holder farmers (1-2.5 acres) who typically plant 1-2 crops each year[17]. The Green Revolution of the 1960s resulted in large increases in the use of high-yielding varieties and complementary inputs like fertilizer, even among small farmers. However, levels of technology investment remain low. Agricultural households commonly produce staples, and consume a significant proportion of their output[18]. They sell the rest of their produce either directly to wholesale markets *(mandis)* within their districts, or to middlemen who aggregate produce and sell it in the market.

There is strong evidence that local markets (at the level of the district, for example) are not well-integrated, because of which the effects of local weather shocks on prices are not completely arbitraged across districts[19].Transportation costs, the short shelf-life of most agricultural produce, and varied tastes for particular produce across states all result in large amounts of price variation between states, and even across districts within the same state[20][21]. Prices in the wholesale market are set using a system of first-price auctions and can, in some cases, involve brokers who facilitate sales.

[17] NSS rounds 55-68.

[18] NSS round 70

[19] I quantify the impact of local shocks on local market prices in section 4.2.

[20] Within-year within-state standard deviation in wholesale prices averages Rs. 143 per 100 kgs of rice and Rs. 108 per 100 kgs of wheat.

[21] There are numerous regulatory barriers to inter-state movement of agricultural produce (Kohli & Smith 2003, Gulati 2012, Allen 2013) that also contribute to this price dispersion.

Farmers and middlemen tend to transport their produce only to the nearest market, leading me to characterize them as price-takers from their own district's wholesale market in this context [22].

Price supports were introduced well before the time period over which I conduct my analyses, so I do not anticipate a "learning period" in my data in which farmers discover and begin utilizing the program. The Indian government has a long history of price support policies. Price supports for staple products began in 1972, as production boomed and prices began to fall. I only analyze the effects of the price support after 1997, when the consumption-side of the program underwent a major overhaul that included, for the first time, targeted subsidies.

2.2 Setting and Implementing Minimum Support Prices

Support prices are announced at the beginning of each agricultural year, prior to planting, and paid at harvest. In June each year, at the time of the early annual monsoon, the Committee for Agricultural Costs and Prices (CACP) of the Central government announces a slate of national Minimum Support Prices (MSPs) for up to 25 crops[23]. However, government procurement at the MSP is a viable alternative only in the case of rice and wheat, which have both been procured at rates of higher than 15% since 1997[24] (Figure 1). As of the 2011-2012 season, procurement of rice and wheat stands at 40.2% and 39.7% of total production respectively.

Support prices are set independently for the two main cultivation seasons in the country, the Winter *Kharif* season (the main rice season[25]), and the Spring *Rabi* season (the main wheat season[26]), and paid out only the harvest period pertaining to that season[27]). The two seasons are distinct: either the rice support price is in effect, or the wheat support price is in effect, and not both[28]. At baseline, we assume that farmers are aware of these prices before they make planting decisions (which occur 2-3 weeks after the main monsoon).

I consider the MSP-setting process to have elements of randomness from the perspective of the farmer, for four reasons, and these in turn validate the parallel trends assumption in the differences-in-differences framework I use. First, the precise algorithm that is used to set prices is not public knowledge, and certainly not known to the potential beneficiaries of the price supports [29]. Second, in addition to the information observed

[22]Despite the lack of market integration described above, we can assume that there are at least some producers in any given district that are able to transport and sell their produce in a neighboring district. To the extent that this small group of farmers has the alternative option of selling in another district at a higher price than in their own (or the MSP), they are less likely to respond to the policy, and will dampen the magnitude of the effect that I find.

[23]Data on Minimum Support Prices Recommended by CACP and Fixed by Government (Crop Year)

[24]In theory, farmers can sell any of 25 crops to various government *mandis* during the harvest. In practice, however, the price support policy focuses heavily on staples, particularly in the period between 1997-2012, the relevant period of study for this paper. In the case of pulses, for example, for which MSPs are regularly announced, under 1% of production is procured (Bhattacharya 2016). For cotton, a key cash crop, the proportion of procurement stands at a low 7% ("Cotton procurement at 2-2.5 million bales", Nov 14th 2015, Business Standard, and data from the Cotton Corporation of India http://cotcorp.gov.in/statistics.aspx).

[25]Planting in June-July, harvesting in Dec-Jan

[26]Planting in Nov-Dec, harvesting in Feb-Apr

[27]For example, the MSP for rice applies only between January and March for the main rice harvest from the *Kharif* season, while the MSP for wheat is effective in the *Rabi* season.

[28]Apart from the fact that the rice MSPs are only paid for harvesting in the *Kharif* season and the wheat MSPs are only paid for harvesting in the *Rabi* seasons, there are only 35 districts that cultivate both rice and wheat in the *Rabi* season (of which only 4 are significant wheat producers) and only 7 districts that produce both rice and wheat in the *Kharif* season (of which none are significant wheat producers). It is therefore unlikely that the support prices for rice and wheat intersect in decision-making within a season. However, farmers may certainly substitute production across seasons, since support prices are known before the earlier of the two seasons (the *Kharif* season) begins. I show this mitigating effect in section 8.6.

[29]While State governments provide recommendations to the CACP, the committee takes into account a wide range of information, including cost surveys from around the country and monsoon forecasts. The CACP describes the following considerations in setting these price supports (Terms of Reference, CACP 2009):

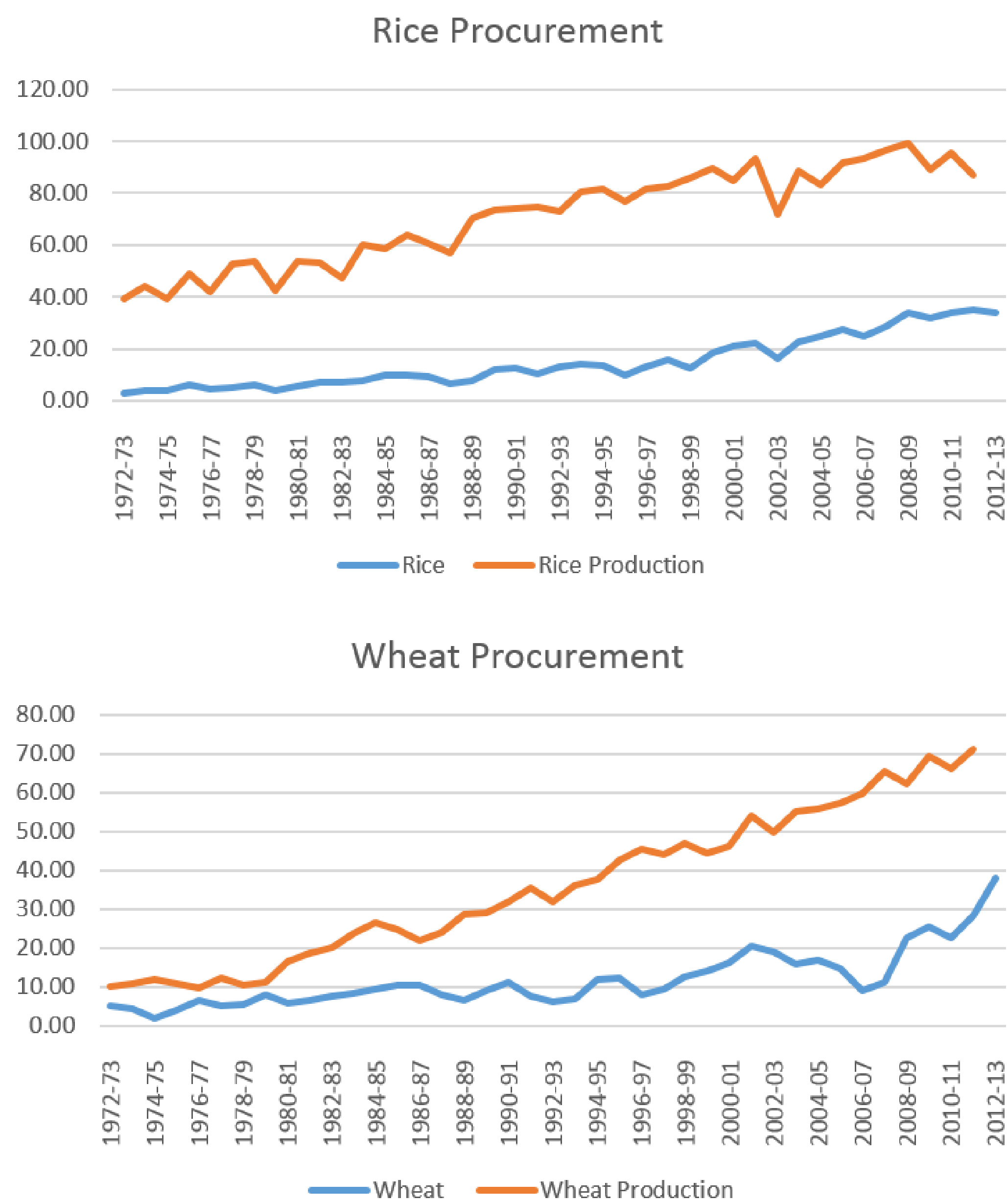

Figure 1: Amount of rice and wheat produced and procured (million tonnes)

and taken into account by the national government, MSPs are set through a political process that introduces some randomness. There is a clear sense that political pressure sets ever-increasing MSPs[30]. Third, it is unlikely that there is meaningful district-specific information encoded into the national MSP announcement that was previously unknown to farmers in that district that could directly influence production decisions. Fourth, I verify that price supports do not correlate with various other metrics that are observable to farmers that may affect production: aggregate early-season rainfall (productivity) shocks[31] and monsoon forecasts (Appendix Table A1.1).

The government serves as an alternative buyer for agricultural output at harvest, setting an effective (but not legislated) price support. At harvest-time, State and Central governments set up *mandis* in which any farmer can sell their harvest directly to government officials at the previously-announced MSP. At the time of the harvest, farmers observe realized prices in the wholesale market and make a decision about whether to sell their crops at the government *mandi* or at the wholesale market, taking into account transportation costs to both.

Since governments do not legislate a price floor, farmers often experience local market prices that are below the MSP in local wholesale markets in some years, but not in others. There are two main reasons I identify for continuing to observe prices below the MSP in some wholesale markets in some years: 1. Not all farmers are aware of the MSPs that have been set, and, as such, those producers do not consider the government price support policy in their planting or selling decisions[32] 2. Even among those who are aware of the MSP while making their production decisions, some might find that the additional transport cost required to take produce to the government *mandis* is too high, and therefore remain non-compliers[33]. It is this population of non-compliers and those with imperfect information who participate in the local wholesale market, in which I observe prices[34].

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1. Cost of production, elicited through surveys,
2. Demand and supply,
3. Domestic and international price trends,
4. Inter-crop price parity,
5. Terms of trade between agriculture and non-agriculture, and
6. Likely implications of MSP on consumers of that product.

[30]MSPs have continued rising steeply in recent years and have never fallen in their entire history, even in periods in which world prices for rice and wheat are falling. I assume, therefore, that individual districts have no influence in setting the national MSP, once state-time trends are accounted for. State governments or the Central government sometimes announce surprise bonuses to the MSP, which are unknown to the farmer at the time of planting (and therefore do not factor into planting decisions).

[31]Since the monsoon begins in the earliest states in late May and announcement of price supports is made in June, it is possible that the aggregate of local-level rainfall shocks across the country is taken into account in setting the support price in the Kharif season, but I show that this is not the case. To do this, I test whether early-season rainfall across the country is predictive of the minimum support price (both in levels and first-differences) for rice and wheat, and find that it is not. Figure A1.1 indicates an increasing trend for real support prices over time for both rice and wheat, despite low (for example, 2012) and high (e.g. 2008) early-season rainfall realizations. Figure A1.2 shows that changes in support prices also show no consistent pattern in response to early-season rainfall. Second, even if there were such a pattern, it would not pose a threat to identification. I rely on local-level variation in early-season rainfall around the national average by including year fixed-effects in my specifications. This implies that changes in the national-level price support, even if based on some aggregate measure of early-season rainfall, are still random from the perspective of the individual farmer in a particular district. This does not pose a problem in the *Rabi* season since the announcement of support prices takes place in June, while early season *Rabi* rainfall only begins to be realized in September. Nevertheless, I present evidence that support prices do not depend on early-season rainfall realizations in both seasons.

[32]Data from the 70th round of the NSS suggests that only 32% of rice-producing households accurately know the current MSP level for rice (39% for wheat). 12 % of rice-producing households and 16% of wheat-producing households reported sales to the government through the PDS system.

[33]Access to government mandis varies widely across districts and states, resulting in uneven access to price supports. I discuss this issue further in section 8.3.

[34]There are, of course, operational constraints to accessing government *mandis* that extend beyond distance. These include

The policy's focus on rice and wheat is the result of the government's overall goal to procure staples and redistribute it at a single subsidized price to low-income households through a network of close to 500,000 ration stores across the country[35]. This paper focuses only on production responses to the support price, and assumes that the consumption side of the program does not vary systematically with production-side factors in the period of study[36].

2.3 The Farmer's Timeline

I gather the details above into a timeline outlining the implementation of the policy for a representative state (Figures 2 and 3).

There are three key takeaways from the timing of implementation. First, the MSP is known (without uncertainty) when planting decisions are being made, and can influence planting and input decisions. Second, early-season monsoon rain is observed before planting occurs, and shocks to early-season rain reflect shocks to agricultural productivity. Third, farmers may form expectations of yield and market price based on monsoon rains, but these remain stochastic at the time of planting.

3 Two-Sector Framework

In this section, I present a two-sector model of allocation of capital and labor between agricultural and non-agricultural production. The model makes several simplifications to the context, but is used to provide useful comparative statics of farmers' responses to productivity shocks arising from local-level rainfall variation, both with and without price supports.

I make the following simplifying assumptions in creating the framework. In Section 3.6, I discuss relaxing these assumptions.

1. That each district behaves like a small closed economy.
2. That within the agricultural sector, a single crop is produced with a single price, and that the price support (when I introduce it) applies to that one crop. This assumption allows me to focus on inter-sectoral labor shifts.
3. That realized prices are known with certainty immediately following the productivity shock - that is, that households observe early-season rainfall, and know the local market price for the agricultural good precisely.
4. That capital and labor are completely mobile across sectors.

the operational hours of *mandis*, potential bribes that need to be paid for the produce to be accepted, and overcrowded warehouses - all of which narrow the complier population and dampen the effect of the policy on producers. I discuss the implications of these in further detail in Section 8.

[35] Unlike the production-side price supports, which are available to all farmers, regardless of land-holding, the consumption-side subsidies are targeted toward poorer households. Rice and wheat are sold at a subsidized price (always below market retail prices) to people who hold Below-Poverty Line (BPL) cards (38% of the rural population), and at an even lower price to the ultra-poor. Consumer prices through the program are set at the national level also.

[36] The resale of rice and wheat procured by the government through ration stores may directly affect farmers' production choices, so I restrict my analyses to a time period (1997-2012) in which there are no major changes in administration and selection of beneficiaries by the government on the consumption side of the program. I discuss potential interactions between the production and consumption sides of the program in greater detail in Section 8.

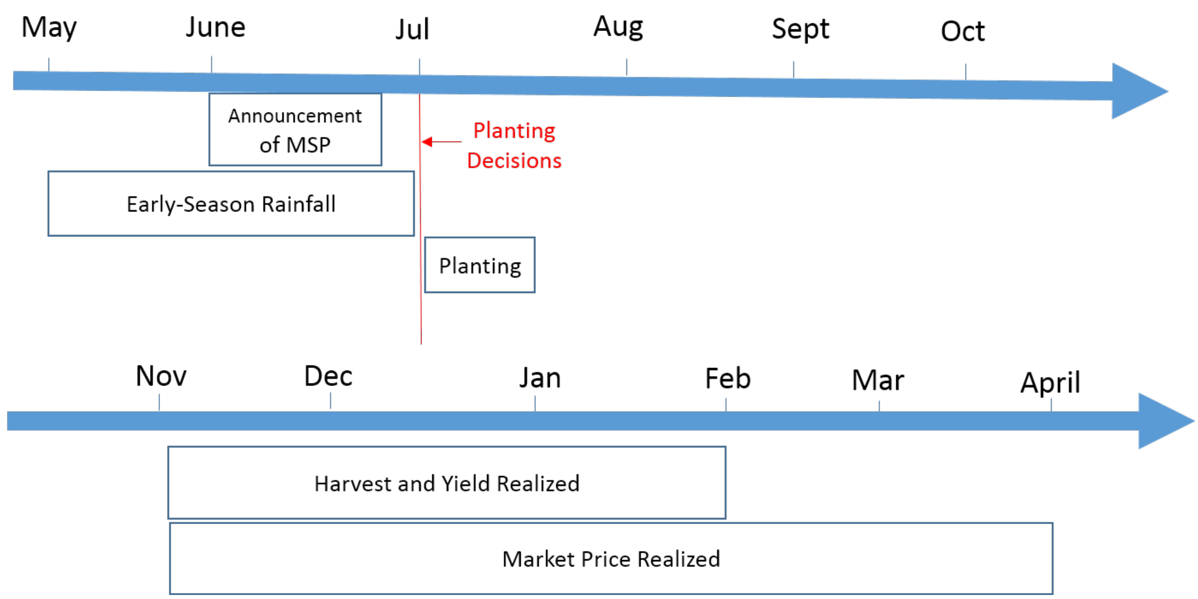

Figure 2: Timeline of events for the *Kharif* season.

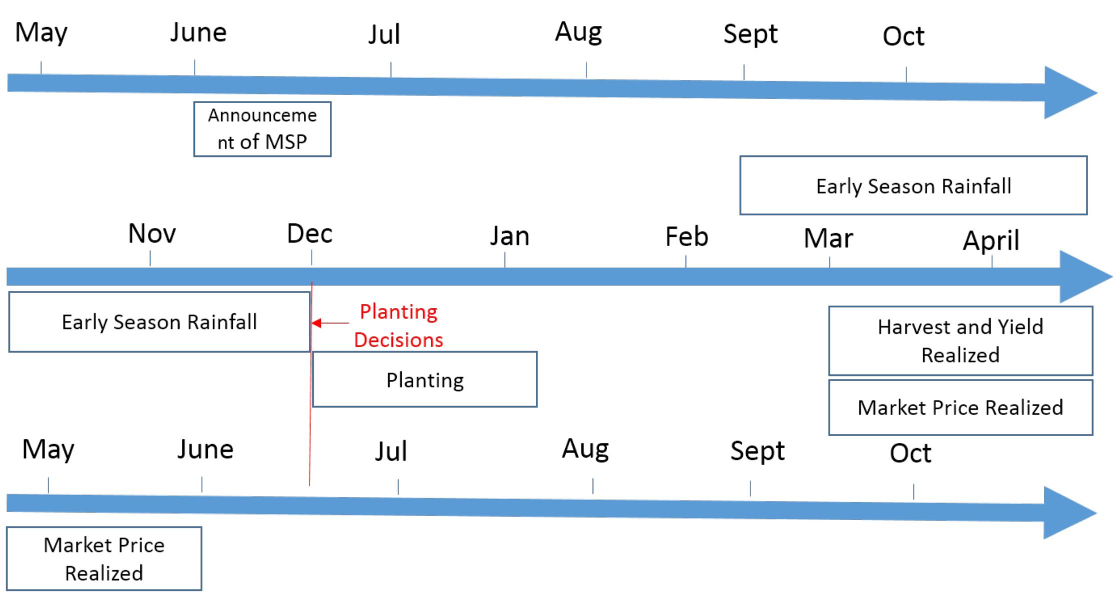

Figure 3: Timeline of events for the *Rabi* season.

3.1 Household Utility Maximization

I begin with a version of the framework without price supports. A representative household h earns income I from renting a stock of capital, K, and labor L, at rates r and w respectively. In turn, the household consumes two goods, an agricultural good and a manufacturing good. It maximizes a standard CES utility function[37] subject to a budget constraint (without credit). That is, the household chooses q_M and q_A to maximize:

$$U_h = [\alpha q_A^{\frac{\sigma-1}{\sigma}} + (1-\alpha) q_M^{\frac{\sigma-1}{\sigma}}]^{\frac{\sigma}{\sigma-1}} \text{ s. t.}$$
$$p_A qA + q_M = I,$$

where p_A is the price per unit of the agricultural output, and the price of the manufacturing good is normalized to 1.
Household optimization then satisfies the following conditions:

$$\frac{G\alpha q_A^{\frac{-1}{\sigma}}}{p_A} = G(1-\alpha) q_M^{\frac{-1}{\sigma}}\,{}^{38} \tag{1}$$

and

$$q_M = I - p_A q_A \tag{2}$$

I combine equations 1 and 2 to derive the optimal quantity consumed of the manufacturing good:

$$q_M = \frac{(1-\alpha)^\sigma I}{\alpha^\sigma p_A^{1-\sigma} + (1-\alpha)^\sigma} \tag{3}$$

[39]

[37] I also show that Cobb-Douglas Stone-Geary preferences, also common to the literature, provide an even more stark version of the comparative statics derived here, due to stronger income effects arising from a subsistence constraint (derivation available upon request). Prior literature (Restuccia et al. 2008, Herrendorf 2013, Lee 2014) suggests that C-D Stone-Geary preferences better model the cross-country variation in responses to agricultural productivity shocks.

[38] Where $G = [\alpha q_A^{\frac{\sigma-1}{\sigma}} + (1-\alpha) q_M^{\frac{\sigma-1}{\sigma}}]^{\frac{1}{\sigma-1}}$

[39] While we use equation 3 in deriving the general equilibrium in this model, an intuitive way to think about the equilibrium arises from examining quantity shares for the two goods:

$$\frac{q_M}{q_A} = \left(\frac{\frac{1-\alpha}{p_M}}{\frac{\alpha}{p_A}}\right)^\sigma \tag{4}$$

The representative household consumes according to the (price-weighted) ratios of the importance of each good in the utility function, downweighted by the substitutability between the goods. The higher the substitutability between the goods (higher σ), the closer the household gets to consuming only one good. If the goods are perfect complements, on the other hand, the goods will be consumed exactly in a 1:1 ratio.

3.2 Producers' Profit Maximization

In the firms' maximization problem, I make standard assumptions of perfect competition and profit maximization among producers in both sectors. Capital and labor are perfectly mobile across sectors and priced at r and w respectively.

Firms in both sectors possess a Cobb-Douglas production technology:

$$y_i = z_i K_i^{\beta_i} L_i^{1-\beta_i},$$

where the z's are industry-specific productivity factors, where the returns to capital in the non-agricultural production function are higher ($\beta_M > \beta_A$).

Firms in each sector $i = M, A$, facing input prices r, w, choose K_i, Li, to maximize profits:

$$\pi_i = p_i z_i K_i^{\beta_i} L_i^{1-\beta_i} - wL_i - rK_i, \tag{5}$$

where p_i represents the price of the output of sector i, and p_M, the price of manufacturing goods, is normalized to 1.

First-order conditions (FOC) from the firms' maximization problem give:

$$\beta_i p_i z_i (\frac{K_i}{L_i})^{\beta i-1} = r \tag{6}$$

and

$$(1-\beta_i) p_i z_i (\frac{K_i}{L_i})^{\beta i} = w \tag{7}$$

for each of $i = M, A$.

The first-order conditions can be rearranged to express agricultural price as a function of inputs in manufacturing, and K_M as a function of L_M:

$$p_A = \frac{\beta_M z_M}{\beta_A z_A} (\frac{K_M}{L_M})^{\beta_M - 1} (\frac{K - K_M}{L - L_M})^{1-\beta_A} \tag{8}$$

$$K_M = \frac{(1-\beta_A)\beta_M K L_M}{(1-\beta_M)\beta_A L + (\beta_M - \beta_A) L_M} \tag{9}$$

3.3 Equilibrium Without Price Supports

First, at equilibrium, the amount of manufacturing output must equal the manufacturing output consumed:

$$y_M = q_M = \frac{E_M}{p_M} = E_M \tag{10}$$

Second, the total capital and labor stock in the economy should be distributed among the sectors[40]:

$$K = K_M + K_A \tag{11}$$

$$L = L_M + L_A \tag{12}$$

Third, the total price of capital and labor used (in the firms' maximization problem) should equal total household income:

$$I = wL + rK \tag{13}$$

Taking FOC from both utility and profit maximization problems, and the equilibrium conditions detailed above, I express the optimal labor allocation to manufacturing, L_M, in an implicit function of the price for the agricultural good, p_A[41] :

$$L_M[\kappa_1 p_A^{1-\sigma} + \kappa_2] - \kappa_2 L = 0 \text{ [42]} \tag{14}$$

where

$$p_A = \frac{\kappa_3 z_M}{z_A}[\frac{K}{(1-\beta_M)\beta_A L + (\beta_M - \beta_A)L_M}]^{\beta_M - \beta_A} \text{ [43]} \tag{15}$$

At first glance, it is clear that p_A mediates the relationship between agricultural productivity, z_A, and labor in manufacturing, L_M, in equilibrium. I discuss this in further detail in Section 3.5.

3.4 Production, Consumption, and Equilibrium with Price Supports

I next turn to the case in which a price support is in effect for the agricultural good. That is, I assume the government purchases as much of the agricultural output as farmers want to sell at the support price p_S, and sells as much of the output as consumers demand at $p_C < p_S$[44]. In this case, the government also absorbs and over- or under-production in the agricultural sector, which implies that in a general equilibrium solution, local agricultural output need not equal consumption.

Demand for manufacturing goods now responds to consumer prices p_C:

[40] With these preference structures and production technologies, it is clear that utility- and profit-maximization require the entire capital and labor stock in the economy to be utilized.

[41] A complete derivation is provided in the Model Appendix.

[42] Where $\kappa_1 = (\frac{\alpha}{1-\alpha})^\sigma$ and $\kappa_2 = \frac{1-\beta_M}{1-\beta_A}$.

[43] Where $\kappa_3 = \frac{\beta_M[\beta_A(1-\beta_M)]^{1-\beta_A}}{\beta A[\beta_M(1-\beta_A)]^{1-\beta_M}}$.

[44] This can easily be extended to the small open economy case by setting $p_C = p_S$.

$$q_M = \frac{(1-\alpha)^\sigma I}{\alpha^\sigma p_C^{1-\sigma} + (1-\alpha)^\sigma} \tag{16}$$

Firms' profit-maximization determines that the optimal ratio of capital to labor in both sectors is mediated by the agricultural producer price:

$$p_S = \frac{\beta_M z_M}{\beta_A z_A} (\frac{K_M}{L_M})^{\beta_M - 1} (\frac{K - K_M}{L - L_M})^{1-\beta_A} \tag{17}$$

I also note that the relationship between capital and labor in manufacturing remains unchanged in this context (equation 9). I therefore substitute equation 9 into equation 17, and obtain a relationship between agricultural productivity, labor in manufacturing, and the level of the price support:

$$L_M = \frac{(\frac{\kappa_4}{p_S z_A})^{\frac{1}{\beta_M - \beta_A}} - \kappa_5}{\beta_M - \beta_A} \tag{18}$$ [45]

In the case with price supports, the producer price in the agricultural sector, p_S, continues to figure in the relationship between non-agricultural labor allocation and agricultural productivity, but is a constant.

3.5 Comparative Statics

In this subsection, I focus on four important comparative statics that showcase the various channels through which productivity shocks affect input allocation across sectors - manufacturing labor allocation, prices in the agricultural sector, manufacturing demand, and agricultural demand[46].

Direct Responses to Positive Productivity Shocks in the Absence of Price Supports: From the base model without price supports, when there is a positive agricultural productivity shock (increase in z_A), agricultural prices fall relative to manufacturing prices (equation 15), and the resulting income effect is stronger than the substitution effect, causing demand for manufacturing goods to increase (equation 3)[47].

As a result, there is an increased allocation of labor to the non-agricultural sector - $\frac{\partial L_M}{\partial z_A} > 0$ (equation 14). This is sufficiently large to overcome the movement of labor into agriculture due to the positive pressure on wages due to higher agricultural labor productivity (equation 7).

The net result is that allocation of labor to manufacturing responds *positively* to increased productivity in agriculture. This has been shown to hold in the case of India, both in prior literature (Emerick 2016, Santangelo 2016) and in the labor response I find to a positive productivity shock in tables 6 and 14 in low-price-support years (when markets behave more as they do in this base case).

Finally, there are two competing effects of higher agricultural productivity on agricultural production in equilibrium. First, higher productivity directly increases production, all else equal. However, from above,

[45] Where $\kappa_4 = [(1-\beta_A)\beta_M]^{\beta_M - 1}[(1-\beta_M)\beta_A]^{1-\beta_A} K^{\beta_M - \beta_A}$ and $\kappa_5 = (1-\beta_M)\beta_A L$.

[46] Detailed derivations of the comparative statics in this section are provided in A3.2.

[47] that is, assuming σ, the elasticity of substitution, is smaller than 1.

we know that the amount of labor dedicated to agriculture falls in response to relatively lower agricultural prices and the resulting increase in manufacturing demand. The net effect of higher productivity on agricultural output without price supports depends on which channel dominates[48].

I next move to the version of the model with price supports.

Responses to Positive Productivity Shocks with Price Supports: When there is a positive agricultural productivity shock, agricultural prices now do not fall relative to manufacturing prices. Therefore, one of the two channels shifting labor into agriculture is weakened, and the second dominates in equilibrium - $\frac{\partial L_M}{\partial z_A} < 0$ (from equation 18). That is, price rigidities are sufficient to reverse the direction of the labor allocation response to positive productivity shocks.

In addition, equation 18 also shows that the level of the price support p_s amplifies the effect of agricultural productivity shocks on equilibrium labor allocations. That, is, for a given positive productivity shock to z_A, the resulting decrease in the labor allocated to manufacturing, L_M, is larger when p_S is higher:

$$\frac{\partial L_M}{\partial p_S \partial z_A} > 0 \tag{19}$$

Finally, agricultural production increases unambiguously with z_A in the presence of price supports; the shift of labor away from manufacturing, coupled with increased productivity, leads to an increase in output - there is therefore no labor channel mitigating the increase in output. Therefore, the presence of price supports (and the resulting increase in agricultural labor use), implies a bigger production boost in response to an agricultural productivity shock in this case relative to the base case without price supports.

3.6 Assumptions

The framework outlined above is clearly a simplification of the Indian support price policy. The key differences between the model and the execution of the policy are as follows:

First and most importantly, Indian districts do not exist entirely in either the regime with, or without price supports. If realized prices are sufficiently high, price supports do not bind and we can expect that the district behaves according to the base case. If realized prices are low, then the district produces according to the binding support price. Adding a layer of complication to this is the fact that farmers do not know, at the time of planting, whether the price support will bind. Farmers in each district can only estimate a probability that they will fall under one regime or another. Therefore, based on these probabilities, districts fall on a continuum between the two models.

In light of this, we expect a decrease in the amount of labor allocated to the non-agricultural sector in high price-support years for two reasons. First, the probability that the price support will bind at harvest for a given district is higher (therefore there is an increased chance of being in the price support case). Second, the level of the price support is higher relative to local prices, which we have shown to amplify the non-agricultural labor response. Combined, both these effects suggest that the differential response of

[48] We know from equations 9 and 14 that $\frac{K_M}{L_M}$ decreases in equilibrium with an increase in z_A. By extension, $\frac{K_A}{L_A} = \frac{K-K_M}{L-L_M}$ increases. Agricultural production is given by $z_A(\frac{K_A}{L_A})^{\beta_A} L_A$, of which the first two terms increase in equilibrium in response to an increase in z_A, while the last term decreases.

non-agricultural labor allocation to an agricultural productivity shock in high- and low-price support years will be negative.

Second, capital and labor are not, in reality, perfectly mobile across sectors. Relaxing this assumption (in the extreme, this would mean that there are separate labor stocks for agriculture and manufacturing) should imply that competition for labor in the agricultural sector in response to positive productivity shocks drives up wages w_A, and demand, prices, and wages in the manufacturing sector, q_M and w_M. There should be smaller labor movements between sectors, both in the base case and with price supports.

Third, not every farmer is a complier - either because of lack of knowledge of the government program, or due to high transport costs to government depots. Because of this the general equilibrium effects will be significantly weaker when taken to the data.

Fourth, the model assumes that the consumption price, p_C, for agricultural goods, is exogenous. This closes off manufacturing demand responses to agricultural prices in the price support case (since demand relies entirely on p_C, which is exogenously set). However, in the Indian Public Distribution System, only a small selected fraction of the population can obtain (a quota of) rice at subsidized prices; the majority of consumers purchase rice on the open market. Open market rice prices, as I show in the next section, decrease in response to agricultural productivity shocks. We know from the model that income effects outweigh substitution effects and manufacturing demand should increase as a result. This, when taken to the data, will dampen the negative manufacturing labor response to agricultural productivity shocks that I derived in the model with price supports.

Fifth, farmers produce a wide variety of crops beyond the two for which price supports are significant, while the model assumes that agricultural output is a single crop. I show that in response to a positive productivity shock, farmers in fact substitute away from staples (perhaps due to utility from diet diversity, and the fulfillment of a caloric minimum intake), which the model cannot capture. This is negated in high price-support years. We may also be concerned that subsitution among crops that are heterogeneous in labor intensity entirely drives the labor market shifts I observe. However, I show increases in raw yield per hectare for staples, indicating an additional increase in input intensity for the crops under price supports - this means that the labor response does not arise simply from a shift to more labor-intensive crops that have price supports.

4 Empirical Strategy

Broadly, identification stems from the interaction between local weather-related productivity shocks, and the extent to which national price supports for rice and wheat keep up with local wholesale prices. Since districts face different weather shocks in different periods, this provides exogenous variation in agricultural productivity and therefore prices at the district-year level[49]. To separately identify the differential effect of productivity shocks on production with and without price supports, I interact these with high and low support prices in a differences-in-differences framework.

[49]Weather shocks can take two forms: rainfall and temperature. Previous work confirms that temperature and rainfall are significant predictors of crop yields (Lobell et al. 2007, Schlenker et al. 2009). However, I avoid using temperature shocks due to their potential direct effect on workers' productivity in the non-agricultural sector (West 2003; Chen 2003; Chan 2009), in favor of focusing on rainfall shocks. Previous work (Dercon 2004, Miguel et al. 2004, Jayachandran 2006, Kaur 2017) has interpreted rainfall shocks as exogenous shifters of TFP.

4.1 Differences-in-differences framework

I consider each district to be a distinct local market within which producers choose to sell either to the market or to the government at harvest-time. I assume that producers have the ability to sell their produce to any wholesale market in their district[50].

Districts vary across time and space in where their realized wholesale market price falls relative to the national MSP. Data from wholesale markets suggest that average district-level harvest-season wholesale prices for rice and wheat in the period 1997-2012 fall below the government's MSP for both rice and wheat for a significant proportion of districts[51].

I show that there is variation over time in whether the MSP is low or high relative to the entire distribution of realized local market prices, which does not necessarily follow any particular time-trend; there are early years with high MSPs relative to the distribution and later years with low MSPs relative to the distribution (Figure 5). This motivates my definition of the MSP as 'low' or 'high' in each year[52](Figure 6). I describe how I determine whether the price support in a given year is high or low in detail in section 4.3.

I combine this with exogenous shocks to agricultural productivity derived from early-season rainfall to determine the how the price support policy affects production and input responses to productivity shocks. I describe how I define productivity shocks in detail in section 4.2.

We can think of each district-year observation as falling into one of four categories:

(A) Low Rainfall, High MSP	(B) High Rainfall, High MSP
(C) Low Rainfall, Low MSP	(D) High Rainfall, Low MSP

In my reduced-form empirical strategy, the effect of the price support policy is reflected in the differential response to good rain (and therefore higher productivity) in low- and high-MSP years. I expect that farmers in districts that experience positive early-season rainfall shocks will anticipate higher agricultural productivity and lower prices (which I verify in detail in the next subsection). When support prices are high, the lower market prices do not factor into production decisions (which are driven by p_S, the level of the price support). Farmers also get an income boost, since the price support is higher than the local market price, exacerbating the effect. They are less likely to cut production in response to positive productivity shocks (good rainfall). As per the table above, that indicates that the difference in staple production in categories B-A will be significantly higher than D-C.

The parallel trends assumption assumes that any direct effect of agricultural productivity shocks on input allocation and crop mix that are not price-related are the same in high and low-MSP years (for example, early-season rainfall being a bigger boost for rice and wheat productivity than for other crops), except for the effect of price supports. Given that local productivity shocks are unlikely to influence whether price supports are high or low on a national level, the parallel trends assumption likely holds.

[50]This, as I have discussed in the previous section, is an approximation, given that producers who are close to district borders may well find that a wholesale market in a neighboring district is closer to them.

[51]That is, district-level wholesale prices at harvest are, in fact, *below* the MSP in approximately 39% of district-year observations for rice and 25% of observations for wheat. 90% of districts are below the MSP in one time period, but above it in another. Figure 4 shows the distribution of rice and wheat market prices relative to the MSP for all district-years.

[52]A continuous version of this variable, the percentile of the support price within the entire distribution of prices, provides similar results, but is more difficult to interpret directly. Results available upon request.

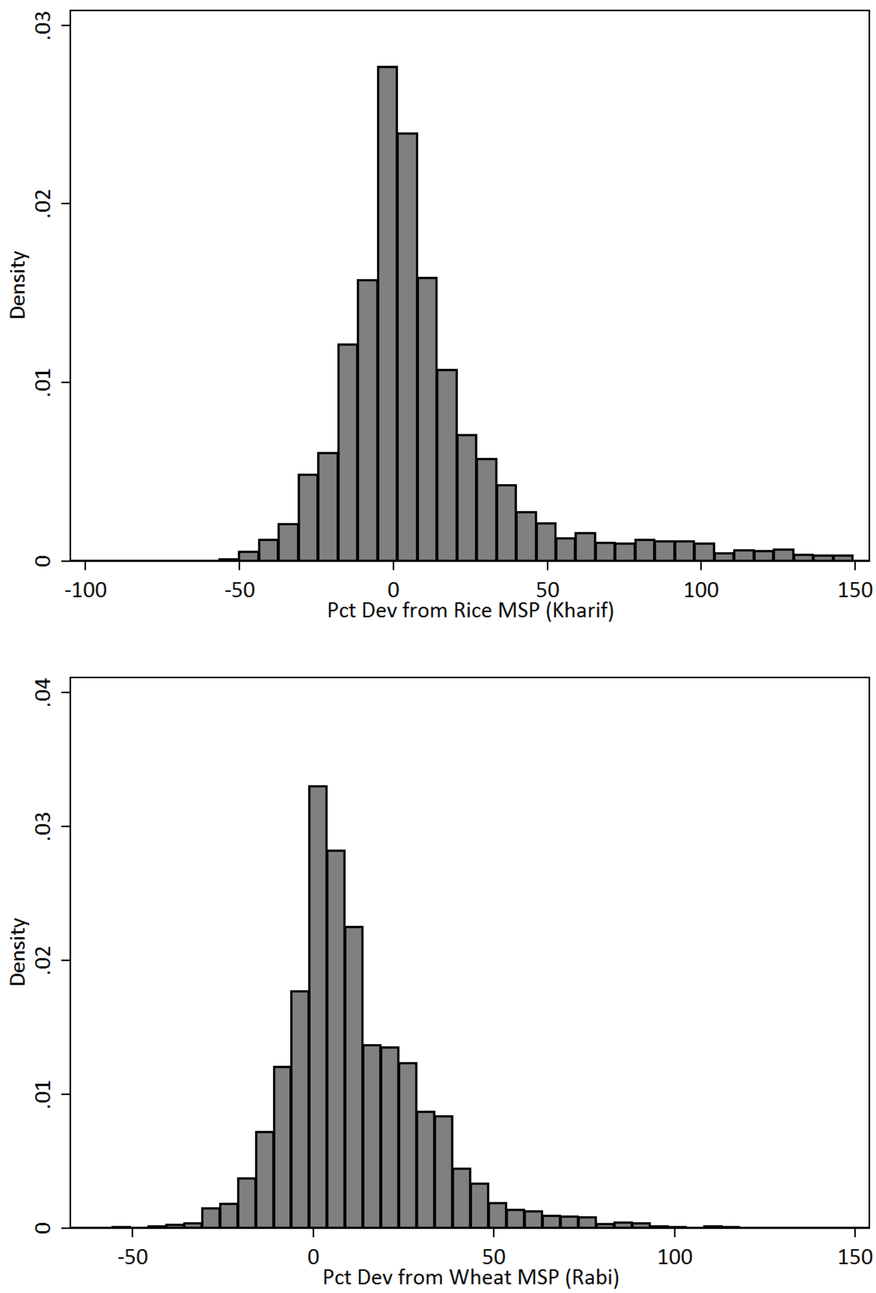

Figure 4: Distribution of percentage deviation of wholesale prices from MSP for all district-year observations between 1997 and 2012.

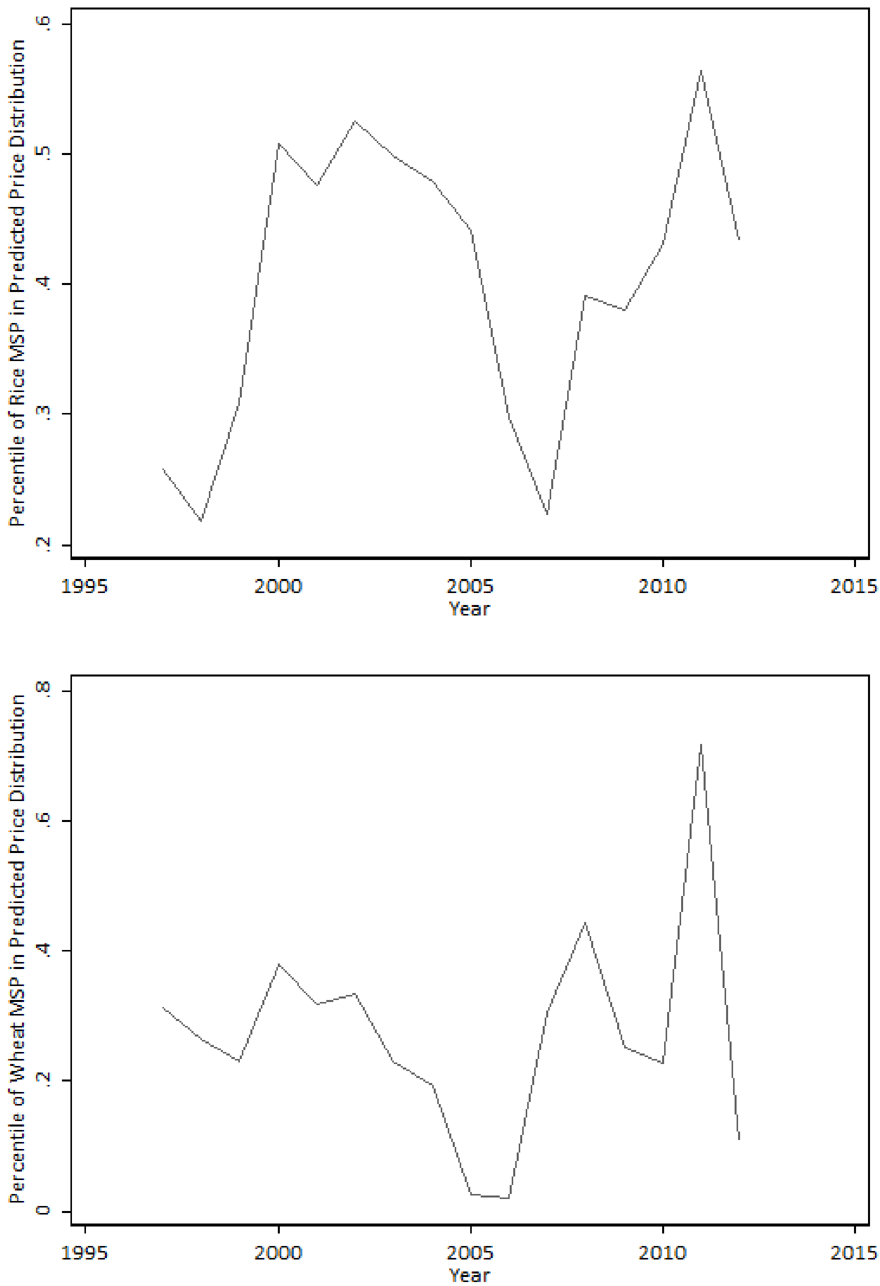

Figure 5: Percentile of MSPs in the price distribution for rice and wheat respectively.

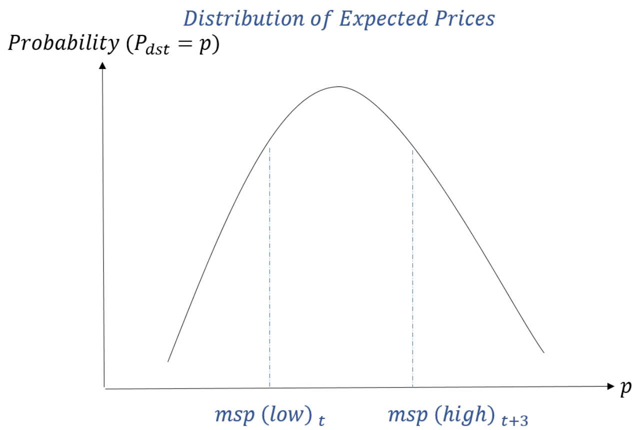

Figure 6: Illustration of variation in where MSP falls relative to the distribution of prices

There are three main challenges that drive my choice of empirical strategy. First, I cannot use a cross-sectional comparison of districts with high and low prices relative to the support price to independently identify the effect of the price support policy. Districts in which realized wholesale market prices fall above the MSP are unobservably (to the econometrician) different from districts in which wholesale prices tend to be low. I therefore use a district-time panel of planting decisions between 1997 and 2012 and include district fixed-effects to compare the response of planting decisions to productivity shocks within the same district in years in which the national MSPs for rice and wheat are more salient to the farmer's decision-making (relatively higher) to years in which they are less so (relatively lower).

Second, using realized market prices at harvest to determine whether price supports are high or low in a given year results in reverse causality. Realized harvest wholesale market prices are, in equilibrium, determined both by planting decisions and market demand for each crop. They are also unknown to the farmer at the time that planting decisions are made. I therefore use price trends for each district to create a (parametric) prediction model for market prices (Section 4.3)[53]. It is important that this prediction be informative *before* planting decisions have been made. These predicted prices form the distribution of anticipated local market prices that determines whether the MSP is high or low in a given year.

Third, a direct comparison between districts with low and high market prices might not estimate the true effect of the support price policy. There are both income and insurance mechanisms at work - people could change planting decisions simply because anticipated income is higher from staple production under the program, or they could respond to the security of having a guaranteed price for rice and wheat, even if the probability of local market prices falling below the minimum support price is low[54]. Because of this, I choose to define all districts in a given year as affected by either a 'high' MSP or a 'low' MSP, and calculate average effects across all districts (both below and above the support price). I do test that the effect of the program is greater for districts in the lowest 30 percentiles of the price distribution in each year[55].

[53]Since each farmer is a price-taker, I abstract away from equilibrium effects in the prediction model.

[54]This would be even more significant if the ability to sell on the local market were limited through informal quotas or limited demand, leaving even farmers in high-price districts with no option other than to sell their remaining produce through the government program, or let it rot for no return.

[55]These districts' market prices typically always fall below the level of the price support in both low- and high-MSP years, and the model suggests that when the price support binds, the higher the level of the price support, the greater the response of farmers in that district. The results are provided in Appendix Tables A2.1 and A2.2.

4.2 Positive Productivity Shocks: Early-season Rainfall

If markets are sufficiently integrated that productivity shocks do not lead to price fluctuations, then price supports would not have a major role in mediating the allocative role of the price mechanism in this context. I test that local market prices do indeed respond to early season rainfall. Figure 7 provides a plot of price residuals (accounting for year and district fixed-effects) against deciles of early-season rainfall within a district. I find that highly negative shocks result in higher local wholesale prices for both rice and wheat.

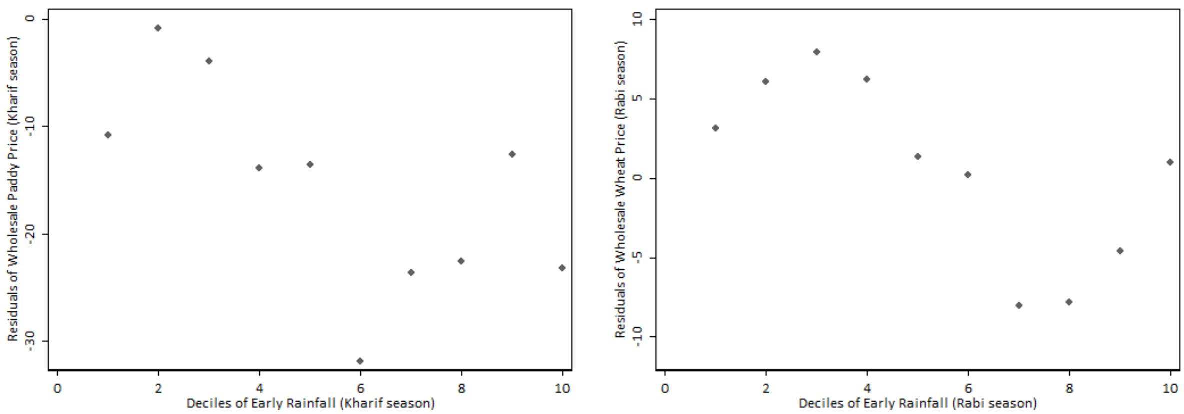

Figure 7: Mean binned residuals of wholesale price of Rice ((*Kharif* season) and Wheat (*Rabi* season) against deciles of early-season rainfall.

Price responses to negative shocks are significant for both rice and wheat, as described in columns 1 and 2 of Tables 1 and 10.

In all main specifications, I define local-level shocks to prices as arising from *negative* deviations from the 40-year long-run average of early-season rainfall for the district, since positive deviations from the LR average are less informative about prices for both crops[56]. I define 'bad' rain - that is, rain that causes prices to increase - as any negative deviation of rainfall of more than 50% below the LR mean of early-season rainfall for the district, and confirm that negative shocks defined this way result in higher prices[57].

I also test that price responses to rainfall shocks are not significantly different in low- and high-MSP years, which means that farmers' local market option responds similarly to productivity shocks in both high- and low-MSP years (Columns 4 and 7 of Tables 1 and 10).

Price responses are large relative to the residual variation in prices (after controlling for year and district fixed effects). A negative early-season rainfall shock causes prices to increase by Rs. 39 per quintal of rice (21% of residual standard deviation in rice prices) and Rs. 27 per quintal of wheat (28% of residual standard deviation in wheat prices). Early-season rainfall is, therefore, an important, and exogenous, shifter of agricultural productivity and therefore local market prices.

[56] Coefficients on positive deviations are small and insignificant in 1 and 10, and this pattern is observable in Figure 7 as well.

[57] This includes 15.7% of observations for rice and 12.1% of observations for wheat. I also conduct a robustness check using a definition of bad rain common to the development literature: defining only the first quintile of observed deviations from the average for that district as a shock to prices. Using both definitions, prices are significantly higher in 'bad' rain years. While I focus mainly on the former in all main results, all results are robust to the latter specification. I present this in more detail in section 8.

4.3 High and Low Price Supports: The Farmer's Prediction of Prices

There is an extensive literature that suggests that farmers adjust to information provided to them prior to the time of planting, based on anticipated profitability[58]. Here, I suggest that farmers use the information they have about productivity to make predictions about prices, and therefore about profitability of the their crop. I also assume that farmers' expectations of market prices given early-season rainfall are rational based on their past observations. I make price predictions in a parametric way, assuming that farmers have knowledge of past rainfall and prices[59], but limited recall. I use farmers' price predictions to classify support prices as high or low in a given year. A given district is 3.4pp, or 8.6% more likely to have a binding realized market price in a 'high' MSP year relative to a 'low' MSP year (Column 3 of Table 1).

To do this, I define farmers' information set in each time period, t, which includes msp_t and early-season rainfall w_t, and realized prices and early-season rainfall for the past α years. That is, they have observed the relationship between early-season rainfall and realized prices for the past α years, and use the parameters that define that relationship to predict this year's market price based on this year's early-season rainfall.

I then use only the data contained in these information sets to make a prediction about this year's market prices during the harvest period for rice and wheat. Specifically, I use a district-specific quadratic function of early-season rainfall[60] , a district-specific time trend, a statextime trend, and district fixed effects, to predict market prices in t.

The empirical specification used in the prediction stage is as follows. I run the following specification using data from $t-1$ to $t-5$:

$$\begin{aligned} p^m_{dst} &= \beta_0 + \beta_{1dst} EarlyRainfall_{dst} + \beta_{2dst} EarlyRainfall^2_{dst} \\ &+ \beta_{3ds}\delta t_{dst} + \iota_{ds} + \epsilon_{dst} \end{aligned}$$

where p^m_{dst} is the local price in a given district d in state s in a given agricultural year and season t. The coefficients on $EarlyRainfall_{dst}$ describe a district-specific quadratic function of the relationship between early-season rainfall and local prices. I also include ι_{ds}, a district fixed effect. δ_t is a district-specific year trend, to account for districts being on different price trajectories over time. Xt_{st} are state-time trends. The error ϵ_{dst} is clustered at the district level.

In creating the specification in this way, I allow for farmers to use other aspects of the prices and data they have observed over the past five years (time trends, district fixed effects that capture the average prices of staples in their district over the five-year period, etc.) in their predictions.

I use the coefficients from the prediction specification to predict prices in time t. Using the predicted prices, I then calculate the percentile of price support in the predicted price distribution. I use median of this value to divide years into 'high' and 'low' MSP years.

[58] Rosenzweig & Udry 2013, Kala 2015

[59] and, in some specifications, past MSP

[60] All rainfall terms are percent deviations from the 40-year long-run average of early-season rainfall taken from 1970 to 2015. Early-season rainfall enters as a quadratic function to allow both positive and negative deviations from the long-run mean to have an effect on prices.

The effect of price supports on production outcomes is robust to various alternatives to this type of prediction. In two alternate specifications (presented in Tables A1.3 and A1.4), I a) exclude early-season rainfall from the prediction, and b) include the level of the MSP in the prediction (so farmers take into account responses of harvest-season market prices to MSP announcements). I also run versions of the specification that vary the size of the information set, α, that the farmer considers in making his prediction (Table A1.5). I discuss these checks in detail in section 8.2.

4.4 The Farmer's Decision Timeline

To make things more specific, the timeline of information and decision-making for the compliant farmer looks as follows:

1. The farmer's pre-planting information set $\mathscr{I}$ includes the realized wholesale market price in the district and information about early season rainfall for the past five years, together with the standard deviation of realized market prices around the prediction. Given the lack of empirical work on farmer decision-making and the extent of information considered in making a decision about this season's planting, this is simply a benchmark model, and I will later examine robustness to varying the size of information set.

2. Based on his information set, he creates a function that links early-season rainfall to realized wholesale market price within his district.

3. Before planting, the farmer observes the signal (early season rainfall), w_{dst} in district d, in state s, in time t.

4. Based on the weather shock, and the prediction model, he knows $p^{\hat{s}}_{dst}$, the expected wholesale market price for the staple crop, and the distribution of potential yields for various crops, $\hat{Y_{jdst}}$.

5. These are all stochastic because of a second, multiplicative weather shock, η_{dst}, which is realized after planting and before the harvest, and affects the final distribution of the market price (but not planting decisions). The realized market price $p^s_{dst} = p^{\hat{s}}_{dst} * \eta_{dst}$, where η is centered around 1. That is, $E[\eta] = 1$.

6. At the same time, the government announces the national-level MSP for the year for the staple crop, msp_t.

7. Given his price prediction and knowledge of the MSP, together with the standard deviation of realized market prices around the predicted market price, the farmer knows the expected probability that realized market price will fall below the MSP. Since the realized market price p^s_{dst} is stochastic even after the initial realization of the weather shock, the distribution of expected prices gives farmers a probability, $\theta|w_{dst}$, that they will eventually sell their harvest at the msp_t.

8. Farmers use these expected probabilities that the market price will fall below the MSP (in which case they expect to sell their crop at the MSP), and predicted prices for rice and wheat, together with information encoded in early season rainfall about the year's relative prices, costs, potential yields, and revenues from various crops to select a portfolio of crops to plant.

9. Then, at harvest time, if the realized market price for the staple p^s_{dst} is higher than the msp_t, farmers sell their output at p^s_{dst}. If it is lower, they sell their output at msp_t.

4.5 Empirical Specifications

I implement the differences-in-differences strategy using the following empirical specification:

$$Y_{dst} = \beta_0 + \beta_1 GoodRainfall_{dst} + \beta_2 GoodRainfall * HighMSP +$$
$$+ \iota_{ds} + \delta_t + Xt_{st} + \epsilon_{dst}$$

In this specification, Y_{dst} are the outcomes of interest in district d in state s in agricultural year t (June to June). These include total area cultivated, area cultivated of staples, area share of staples and other crops, yield, and production[61]. I include ι_{ds}, a district fixed-effect, to control for time-invariant district heterogeneity, such as suitability of the district to grow staples, terrain, how urban or rural a particular district is, average market prices in the district, and so on. δ_t is a year fixed-effect to isolate the effect of high MSP from other changes in production from one year to the next. Xt_{st} are state-time trends that aim to account for the potential influence of any particular state on support prices. Errors ϵ_{dst} are clustered at the district level.

5 Data

I rely on various sources of data at the district-,household-, and firm-level.

In combining data sources, I first deal with the issue of district boundaries changing and new districts being created in the time period of interest. To do this, I aggregate split districts into their original parent district prior to the split, weighting outcome variables by total land area of the split districts where appropriate[62]. My sample contains 469 districts after aggregation. I limit my analyses between the 1997-98 and the 2012-13 agricultural seasons.

5.1 District-time Panel Data

District-time panel data comprise the main data in this paper. These types of data cover all sources of variation over time in prices and rainfall for the empirical analysis, as well as information on district-level planting patterns that change over time.

Data on cropping patterns are important for assessing the first-order responses to the price support policy. The government[63] collects information on area planted and quantity produced for various crops for each district in each season in each year for all districts in India -these are known as the Area Production Yield (or APY) data[64]. I derive area cultivated and raw yields (output per unit area) for each crop in each district-season-year from this dataset. For further analysis on changes in cropping patterns, I classify crops into four main categories: other staple crops, pulses, cash crops, and spices.

[61] I run specifications in levels rather than logs, to allow for switching into and away from producing staples. The data suggest that this pattern is fairly common. Of the districts covered, 74 rice-producing districts and 97 wheat-producing districts report zero production of the staple crop in the *Kharif* season for rice and in the *Rabi* season for wheat in at least one year, but not in all years.

[62] Districts that exchanged portions of their land area with each other (for example, by one district giving a block to another district), are also aggregated.

[63] Directorate of Economics and Statistics of the Ministry of Agriculture and Farmers' Welfare

[64] For a few states in a few years, missing APY data has to be supplemented with Land-Use Statistics Data instead, which does not provide production data. Minor crops that comprise less than 1% of the cultivated area in a district are excluded for a few state-years in the LUS data, due to the sheer number of crops.

Rainfall data allow me to identify which districts face rainfall shocks that affect predicted market prices. I obtain monthly precipitation data at 0.5° resolution[65], which I aggregate to the district level[66]. I use total precipitation in the months of May and June for the *Kharif* season, and September, October, and November for the *Rabi* season, to define pre-planting shocks to agricultural productivity[67].

I use wholesale price data aggregated to the district-level as a measure of local market prices. I use these data, together with rainfall data, to predict harvest-time market prices for each district and create a distribution of anticipated prices for all districts. Daily wholesale price data are sparse in India, particularly in the period prior to 2005. I first compile all available price data for rice and wheat across markets in India reported by AGMARKNET (the number of markets and the number of districts covered varies over time, and currently stands at 3245 wholesale markets across the country)[68]. I average observed daily wholesale prices over the harvest period for each season[69]. I convert prices into real terms using the World Bank's GDP deflator.

Input data are gathered from three rounds of the Agricultural Census Inputs Survey, and cover variable inputs by crop - use of high-yielding varieties, fertilizers, and proportion of area irrigated for rice and wheat.

I eliminate all districts that report no rice or wheat production in the relevant seasons in years of my data. My final sample comprises 5,113 (91% of area under rice production) district-year observations for rice, and 4,707 (94% of area under wheat production) district-year observations for wheat.

5.2 Repeated Cross-sectional Data

Households: The National Sample Survey (NSS) consumption/expenditure modules for rounds 55 to 68 are repeated cross-sectional household surveys that are representative at the district-level. I focus on households surveyed during the *Kharif* and *Rabi* harvest months. The surveys provide detailed information on per-capita household consumption at harvest, an estimate of the number of crops produced by each household during the period of this study, and whether the household produces rice or wheat[70].

In many analyses that use these data, I focus on households that consume rice (*Kharif* season) and wheat (*Rabi* season) out of home production, indicating that they are producers of staples[71].

Individuals: The NSS employment survey rounds 60-68 also provide weekly information on labor supply and

[65] Climatic Research Unit of the University of East Anglia

[66] I calculate measures of monthly rainfall (in mm) at the district-level by superimposing these data on India's district boundaries and calculating means across all 0.5° cells that fall within each district.

[67] In order to define shocks to early-season rainfall more precisely, I calculate percent deviations of each district-year observations from the 40-year long-run district average of precipitation.

[68] Given the low coverage provided by AGMARKNET data, I supplement their wholesale price data using price data, where available, from the ICRISAT meso-level dataset, which covers all districts in 19 major states in India.

[69] January through March for the *Kharif* season and March through June for the *Rabi* season. Wholesale prices rarely move both above and below the price support in a single harvest period for a given district, and that there is little price-variation in markets during the season. This drives my decision to use mean wholesale prices for the entire harvest period for each district to construct my measure of local market prices.

[70] The data distinguish between home production and production from external sources. If the household reports consumption out of home produce of any crop, I assume that it produces that crop. This also includes products made from that crop - for example, I assume that if a household consumes wheat flour from home production, that it produces wheat.

[71] Some households might, particularly in response to the price supports, exclusively sell their staple produce to the market, and consume staples purchased from PDS or on the open market, in which case they would not be included in my sample. To the extent that my analysis excludes such households, my estimates are a lower bound on the effects of the price support on harvest-season expenditure by staple producers.

wages throughout the agricultural cycle. I am able to distinguish between agricultural and non-agricultural time-use. I also calculate average daily wages from these data.

I focus on non-urban households in the agricultural sector surveyed during cultivation periods in the agricultural cycle, when labor supply is likely to be most responsive to incentives in the form of price supports. The survey provides a rich set of household- and individual-level control variables.

Firms: The Annual Survey of Industries data are repeated cross sections between 2002 and 2009 that survey all firms with above 100 employees, and a random sample of 1/3 of smaller firms, including both formal and informal firms. These data are able to validate my results on how labor utilization and output by non-agricultural firms respond to agricultural price supports. These data contain detailed firm-level information on characteristics, inputs, outputs, investment, capital, and employment.

I focus on non-urban firms. As a robustness check, I eliminate firms that use agricultural output as their inputs.

5.3 District-level Snapshot

Crop suitability measures[72] use soil, topographic, and climatic data to estimate suitability distributions (created as an index with a maximum value of 100 and a minimum value of 0) for a variety of crops for each 5 arc-minute grid cell. I obtain baseline suitability indices for 16 of the most prevalent crops in India, including rice and wheat. I aggregate suitability measures for each crop to the district-level[73], and create absolute and relative suitabiity measures[74].

Districts vary widely in their innate suitability for growing rice and wheat, but are all incentivized to grow staples through the government's national MSPs. These suitability indices can be considered a time-invariant baseline characteristic for each district. It is therefore informative to understand how growing patterns and crop yields in low-suitability districts change as a result of price supports, and how the gains from the program are distributed. The fact that low-suitability districts show no response to the program also serves as an additional test that the results derive directly from the program rather than some other random unobserved variation.

6 Results and Discussion

The set of results presented here are from the differences-in-differences framework. The preferred specification defines high and low support prices according to farmers' price predictions based on a five-year recall of local market prices and productivity shocks.

The first coefficient provided in each table (on the indicator for "Good Rain") describes the direct effect of a positive productivity shock on the outcome. The second coefficient, on the interaction term between good rainfall and high MSP, is our coefficient of interest. This estimates the differential production response to good rainfall (and therefore lower prices) in high MSP years relative to low MSP years. The last row of every table gives readers a sense of the magnitude of the effect: it shows the effect as a proportion of the mean of the dependent variable. I refer mostly to these magnitudes in the rest of this section.

[72] From the Global Agro-Ecological Zones database collected and disseminated by International Institute for Applied Systems Analysis (IIASA) and the Food and Agriculture Organization of the United Nations (FAO)

[73] I take an average of the Suitability Index across all 5-minute arc grid cells whose centroids lie within the district boundary.

[74] Details are provided in the Data Appendix.

6.1 Agricultural production

The first set of results in Tables 2 and 11 cover five measures of agricultural production related to the staple crop: the area (hectares) planted with the staple crop in relevant season, the share of cultivated area devoted to the staple crop, total area cultivated across all crops (the extensive margin of production), and yield per unit area (tonnes per hectare) and total production of the staple.

Staple Area Planted and Area Share: The model suggests that the effect of good rain on staple production comprises two opposing effects - first, there could be an anticipated increase in rice yields that may lead farmers to increase area cultivated until the expected return from the marginal hectare planted is zero. However, the positive productivity shock also indicates lower prices for rice (as shown earlier in Table 1) , which puts pressure on farmers to decrease area cultivated, since both the average and marginal return to each unit of produce is now expected to be lower.

The coefficients on good rain in columns 1 and 2 of Table 2 suggest that, for rice, the second effect outweighs the first marginally: area share devoted to rice decreases in response to a positive productivity shock when price supports are low. From Column 3, the effect of good rainfall on total area cultivated (coefficient on “good rain”) in low price support years is not statistically significantly different from zero, indicating that the two effects approximately offset each other on the extensive margin. For wheat (Table 11), the coefficient is positive and significant - good rainfall, in the absence of high MSPs, results in an overall increase in wheat area cultivated - the effect size is about 8% of the mean.

Now we turn to the interaction of productivity and price supports. Here, in the presence of price supports (i.e. when price supports are high and more likely to bind), the price that producers can expect for the staple crop remains stable in response to positive productivity shocks, rather than falling. This should lead to an unambiguously positive interaction effect, which is indeed the case. Columns 1 and 2 of Table 2 show that rice area planted increases 3.3% (3,342 hectares on average) in response to productivity shocks in years in which price supports are high relative to years in which they are low. Column 3 indicates no movement in the total area cultivated in the *Kharif* season. Taken together, these two results indicate that farmers shift land into the production of rice, but do not change the amount of land they cultivate on the extensive margin in response to price supports. I corroborate this by looking at area shares of rice (as a proportion of total area cultivated in the *Kharif* season) in column 2, which show an increase of 6.6%.

There are no shifts in area and area share of wheat in response to high support prices in the *Rabi* season. Columns 1 through 3 of Table 11 show no change in both land area devoted to wheat and total area cultivated in the *Rabi* season in response to good rain in high-MSP years relative to low-MSP years. However, results in the following sections show that the policy has bite among wheat producers too, even when area cultivated and area share remain unchanged.

Yield and Production of Staples: According to the model, farmers may respond to productivity shocks by devoting various kinds of capital or labor to agriculture. The direct effect of a positive productivity shock on raw yield and production within agriculture (that is, not controlling for inputs) are therefore determined in equilibrium according to the allocation of input across sectors. A positive rainfall shock serves as a Hicks-neutral boost to agricultural productivity and, therefore, yields. However, the model suggests that, in response to agricultural productivity shocks, more labor is allocated towards manufacturing (due to increased manufacturing demand), which decreases the amount of labor per unt area available to work in agriculture, leading to decreased yields for the staple crop. In columns 4 and 5 of Tables 2 and 11, I show that the latter effect dominates, and that raw yields fall in reponse to positive productivity shocks.

I now consider the interactive effect of productivity shocks and high price supports on yield and production of rice and wheat. According to the model, more labor is allocated to agriculture when price supports are binding. This should have an unambiguously positive effect on yields and production, and therefore a positive interaction effect between high price supports and positive shocks to agricultural productivity. I find an increase in raw yield of rice (production per hectare) of 7.2% when price supports are high (Column 4 of Table 2). Given the expansion in the area planted with rice, which we expect to be less productive land on average, the increase in yields suggests a reallocation of inputs towards rice as in the model, which I verify by looking at labor supply in agriculture in the next subsection. The expected return to investing in these inputs is now higher (due to stability of producer prices in the face of positive productivity shocks when price supports are high).

Coupled with the increased area planted with rice, the amount of rice produced (Column 4 of Table 2) increases by 8.5% in response to good rainfall in a high-support year relative to a low-support year, on average.

Wheat production also increases between 9.7% (Column 5 of Table 11). This is driven by a significant (and large) increase in raw yields of wheat of between 8% (Column 4 of Table 11).

Crop Mix: My model abstracts away from the crop mix decision of the farmer by considering a single agricultural output. However, Indian farmers often grow more than one crop, and the decision about how to allocate resources across crops is endogenous to the existence of price supports.

I find, in Table 3, that a positive productivity shock in low-suport years, leads to a shift in area share from rice production in the *Kharif* season to risker, higher-return crops like pulses and oilseeds. I interpret this as the direct effect of positive productivity shocks on crop choice. There are a number of potential micro-foundations for this result: 1. Farmers might consider rice to be a giffen good in production: after reaching a basic amount of production and satisfying a basic caloric requirement (which happens more easily when there is a positive production shock), they might want to consume a more diverse diet. Second, farmers might be more willing to take on risk once their basic staple needs are met. Third, other crops may be more sensitive to early-season rainfall, both in productivity and prices.

I now move to the interactive effect of price supports and positive productivity shocks on crop mix responses. In the presence of high price supports, I find that, relative to low price-support years, there is a shift in crop mix towards the staple crop, rice. The overall effect on rice area shares in high price supports years (summing the direct and interaction terms in Column 2 of Table 2) is effectively zero: farmers do not shift away from rice in response to positive productivity shocks when price supports are high.

Crop Suitability and Responses to Price Supports: As described in section 5, I calculate a measure of relative crop suitability that is akin to a measure of marginal cost of cultivating a unit of land with each of these staple crops *relative to planting other crops*. This is more suitable than a measure of absolute suitability given that landowners and making crop choices on the intensive (as well as extensive) margins. I use these measures for two purposes; first, to discern whether there is heterogeneity in gains from the program between low- and highly-suitable districts. In a policy that prioritizes staple crops over others, my results show that gains are distributed only among districts that are better able to switch into staple-production (Tables 4 and 12).

Second, I use this to verify that my estimates are driven by exposure to high price supports for rice and wheat specifically, rather than general (and universal) changes in agricultural production patterns that happen to correlate with high price supports.

6.2 Consumption

When there is a positive productivity shock, the shift of labor out of the agricultural sector and the resulting increase in agricultural wages, together with lower prices for agricultural produce, imply that the effects on household income are ambiguous. The most direct effect of the support policy on agricultural households is through monthly per-capita expenditure at harvest, when production and market prices are realized. Without a direct measure of income, this is the best proxy measure available. I first consider the direct effect of a positive productivity shock, which has two effects on consumption: it increases consumption through greater productivity, but gives farmers lower prices for their output. Overall, I find that households do not consume more in response to a positive productivity shock (Tables 5 and 13).

I then look at the effect of price supports on consumption responses to positive productivity shocks. Rice- and wheat-producing households surveyed at harvest both show no differential increase in monthly per-capita expenditure in response to good rainfall in high-MSP years, relative to low-MSP years (Tables 5 and 13). Agricultural households produce more price-supported output in high MSP years, but receive lower wages for the labor they sell to other producers (which I discuss in the next section). These opposing effects comprise the null result.

However, I find that rice- and wheat-producing households consume more in high price support years relative to low price support years, while agricultural households that do not produce these crops show no such increase. This negates the concern that the program is simply implemented badly, or that farmers face costs that are too high in accessing it.

6.3 Spillovers to the Non-Agricultural Sector

The increases in yield and production for both rice and wheat indicate a shift of inputs towards staple cultivation. Chief among these is labor. I find no increase in the use of irrigation, high-yielding varieties, or fertilizer in response to price supports for rice and wheat (Table 8)[75].

Labor Allocation Across Sectors: Prior literature suggests that Hicks-neutral or labor-saving productivity shocks can lead to industrial growth (Bustos et al. 2012, Emerick 2016, and Santangelo 2016) through reallocation of labor into the non-agricultural sector[76], in line with comparative statics from the model.

I consider the labor allocation of non-urban households in agriculture using the NSS employment surveys. I find, first, that my results hold true to previous work on the interlinkages between the agricultural and non-agricultural sectors - good rainfall results in an 8pp increase in an indicator for non-agricultural work for the week during the cultivation season (an approximately 35% increase for the typical agricultural household) (Column 3 of Table 6).

I then consider the interaction between the price support policy and labor responses to productivity shocks. I do find that price support policies completely negate the movement out of agriculture by providing incentives to allocate labor to agriculture. In Column 2 of Table 6 I use an alternative definition of labor allocation, the number of days worked in agriculture, and find a 9.78% increase (similar in magnitude to the indicator

[75] This could be in response to low barriers to procuring heavily-subsidized inputs even in the absence of price supports

[76] The latter two papers explicitly document this pattern in response to weather-related positive productivity shocks in India.

outcome).

I note that this pattern emerges even in the case of wheat, a significantly less labor-intensive crop, though, as anticipated, magnitudes are lower (Table 14). I also find that, in the case of wheat, the pattern applies only to men and not to women. I present results here only for the men in the sample. This is, however, entirely unsurprising given that wheat production (to a much greater extent than rice production) tends to exclude women from the process, particularly during cultivation[77].

Occupational Choice: I then check which sectors see the largest decreases in labor allocation in response to productivity shocks in the presence of high price floors, and find that manufacturing and construction (key non-agricultural sectors in rural areas) are affected the most (Table 7).

This assuages any potential concern the labor movements are driven by fluctuations in forced entrepreneurship (which is often reported as non-agricultural employment when agricultural labor demand might be low).

Wages: Finally, I consider the effect on daily wages in both sectors. While the model assumes perfect labor mobility, any frictions in the labor market will cause wages to diverge across sectors. At baseline, wages in the non-agricultural sector are significantly higher than in the agricultural sector.

Coefficients on "good rain" in Columns 3 and 6 of Table 6 show that wages in the agricultural sector increase, and wages in the non-agricultural sector decrease in response to positve productivity shocks, as a natural extension of the labor market shifts I dicussed in the previous subsection. This indicates that falling prices in the agricultural sector and higher demand in the non-agricultural sector in response to positive productivity shocks encourage labor movements that lead to more equal wages across sectors.

I now turn to the differential effect of positive productivity shocks in high-support years relative to low-support years. Wages are higher in equilibrium in the non-agricultural sector during the cultivation season under higher price supports, corresponding with the negation of labor movements out of agriculture. This is especially true in response to the rice price supports, in which there is a 23% differential increase (Rs. 30.5) in non-agricultural daily wages in response to high price supports (Column 5 of Table 6).

A similar estimate for wheat is insignificant, though it moves in the right direction in conjunction with shifts in labor allocation (Column 5 of Table 14).

Labor Use from Industry Data: I use the Annual Survey of Industries (ASI) cross-section of firm-level data for rural firms to confirm that labor is reallocated from firms towards agriculture when rice support prices are high[78]. I find a fall in manufacturing worker-days for open[79] rural firms in response to agricultural productivity shocks in high price support years. This corresponds to the decrease in labor supply from the household surveys (Column 7 of Table 6). This strengthens the argument that price supports have direct effects on labor use in non-agricultural firms.

Interestingly, knowledge of worker-types in the data helps me identify that this effect is driven by a decrease

[77]Chen(1989) points out that women participate in tasks such as weeding, winnowing, drying, storage, and husking or milling, most of which are done at harvest-time. She also states that mechanization has displaced women from even these tasks, and that the shift to chemical fertilizers has shifted women away from a key cultivation-period task: manure-spreading.

[78]Since the data are reported at an annual level, I cannot distinguish between the effects of rice and wheat price supports, and so I choose to focus on rice price supports.

[79]To the extent that firms shut down due to lack of access to labor, or higher wage rates, my estimates are a lower bound.

in total worker-days of 17.8% for contract laborers, which is precisely the margin of adjustment for workers who divide their time across sectors. There is no such effect for permanent employees of these firms (Columns 8 and 9 of Table 6).

Output from Industry Data: Finally, I test the direct impact of price support policies on output in the non-agricultural sector using the ASI data. I find that gross output decreases by 2.6% of a standard deviation in high price support years in response to a positive agricultural productivity shock (Column 1 of Table 9). Value-added measures (Column 2) provide results of roughly similar magnitudes, though these estimates are noisier.

These results suggest that the crowding out of labor from non-agricultural allocation in response to high price supports has a concrete effect on production in the non-agricultural sector, at least in the short run.

7 Implications for Agricultural Productivity

Based on the results up to this point, I find that high price supports for rice and wheat crowd out labor allocation to, and output in the non-agricultural sector. However, the increase in labor usage in the agricultural sector may, in fact, be productivity-enhancing in the agricultural sector. To examine this, I quantify the effect of increasing labor usage in the agricultural sector on agricultural productivity (in the form of agricultural TFP). I use an aggregate agricultural TFP measure common to the literature, the Tornqvist-Theil Index[80]:

$$ln(\frac{TFP_t}{TFP_{t-1}}) = \frac{1}{2}\sum_i (R_{it} + R_{it-1}) ln(\frac{Q_{it}}{Q_{it-1}}) - \frac{1}{2}\sum_j (S_{jt} + S_{jt-1}) ln(\frac{X_{jt}}{X_{jt-1}})$$

Where R_{it} refers to the revenue share of output i in time t and S_{jt} refers to the cost share of input j in time t.

This index allows us to not only capture changes in quantities produced of various crops and quantities used of various inputs, but also any associated changes in input and output prices. These price changes are particularly important since I have already shown that wages respond to the existence of high price supports in accordance with the movement of labor.

I calculate this index for each district for each year in my data for which the NSS modules are available (from which I extract the district-level prices of 14 different crops[81] that I use), and use the same differences-in-differences framework to examine the effect of the policy on agricultural productivity.

I find an increase in agricultural TFP in response to a positive agricultural productivity shock, as anticipated (the coefficient on good rain in column 3 in Table 9). Turning to the interaction term, I find that the increased use of labor in agriculture in response to the higher price support actually decreases agricultural productivity by 0.82 of a standard deviation, negating the positive productivity effect of the shock.

[80] Diewert 1976, Caves et al. 1982, Rosegrant & Evenson 1992, Murgai et al. 2001. This index provides an exact measure of technical change for linear homogeneous translog function that approximates - by a second-order Taylor polynomial - the Cobb-Douglas production function that I use in the model.

[81] Details about the crops used and data sources for this analysis are given in the data appendix A4.2.

However, there are clear data limitations that deem my estimate a lower bound, the key of which is the lack of annual data on district-level input quantities and prices. Instead, I use input quantities for a single year, in which the price support for rice is low, for all inputs other than labor. I use input prices at the state, rather than district, level to calculate cost shares of various inputs (other than labor). Then, to the extent that competition for inputs other than labor also increases simultaneously, pushing up their prices, or that quantities used of these inputs increase when price supports are high, my estimates do not take that into account, and are therefore a lower-bound estimate of the effect of price supports on agricultural productivity.

8 Potential Confounds and Robustness Checks

8.1 Defining High and Low Early-Season Rainfall

In the main specifications, I define rainfall shocks in the two seasons to be a greater-than-50% negative deviation from the 40-year average of early-season rainfall. I also use one alternate specification of good rainfall common in previous literature (Jayachandran 2006; Kaur 2017) that provides a weaker price differential between periods of 'good' and 'bad' rainfall[82], and is therefore more conservative. I define the first quintile of observed deviations from the average for that district as a shock to rainfall and therefore prices.

I present results using this alternate specification in Table A1.2. I find that results all follow with similar magnitudes as in my main rainfall specification, and remain significant.

8.2 Including Different Elements in the Farmer's Information Set At Planting

I test the robustness of the production responses to including different amounts of information in the farmer's information set at the time that planting decisions are made. Table A1.3 provides results for the five main agricultural production outcomes from three prediction methods (based on varying the elements in the farmer's information set) for the main rice production (*Kharif*) season. In the first column, support prices and rainfall do not figure into price prediction (so farmers base their price expectations merely on district-specific time-trends in prices). The second allows predictions to take into account the district-specific effect of rainfall on prices, and is the preferred specification in the main tables of the paper. The third specification accounts for both minimum support prices and rainfall in making price predictions. I show that these key effects of the policy generally move in the same direction and are of the same approximate magnitude for all three specifications. The same is true for wheat (Table A1.4).

I also test that the production results are robust to changing the number of years of information retained in the farmer's memory. I do this by testing a three-year and a seven-year recall period for rainfall and market prices for the farmer, and find the same increase in input intensity aross specifications (Table A1.5).

8.3 International Prices

If farmers plant rice and wheat for export, prices for staples in international markets could affect planting decisions. This could affect my empirical strategy if high MSPs correlate with higher prices on the world market. There are four reasons to think that this not the case. First, the trends in world prices and support prices (in real terms) do not coincide (Figure A1.3). Second, access to world markets should not

[82]The average price differential between periods of good and bad rainfall is Rs.26 per 100 kg for rice, and Rs.16 per 100 kg for wheat, compared to the main definition of rainfall shocks, in which the differential was Rs. 39 per 100 kg for rice and Rs. 26 per 100kg for wheat.

change relative to local-level early-season rainfall shocks. Third, farmers very rarely sell directly for export[83]. Fourth, I check whether the effects of a price support for rice on agricultural production remain in the time period between October 2007/April 2008 and September 2011 (Sharma 2011)[84], when there was a rice export ban across the country, and find that they do (Figure A1.4 illustrates the effect of the ban and Table A1.6, Panel A provides results)[85]. I also analyze the effects of price supports on wheat cultivation in the period Feb 2007 to May 2010 This corresponds to agricultural seasons 2007-2008 to 2009-2010., which coincided with a ban on wheat exports (Sharma 2011), and find similar overall patterns (Table A1.6, Panel B).

8.4 Consumption Side of the Program

Rice and wheat procured from the program are resold at subsidized rates to households below the poverty line. It is possible that years in which procurement is high due to relatively high support prices are a o years in which more is available at subsidized rates to households. Households then sell a larger proportion of the staples they produce (at the high government support price) and then purchase the max consumption quota (or the household's requirement, whichever amount is lower) through the program at subsidized rates. However, that effect functions at the post-production sale margin (the choice of whether to sell or to keep and consume). Any effect on the extensive margin of staple-production would be, if anything, negative.

8.5 Program Implementation

We might also be concerned about uneven program implementation across districts within the country. As mentioned in Section 2, there are multiple reasons for differential access to government purchases of foodgrains, the key of which are variation in the density of government depots (and transportation costs farmers face in taking their produce to the market), and anecdotal reports of delayed depot openings, delayed payments, and other operational constraints[86]. The empirical strategy I use assumes that harvest-season transportation costs and program implementation do not vary in a systematic way within a district with early-season rainfall. To the extent that these constraints are present but unresponsive to early-season rainfall, my estimates form lower-bound estimates for a well-implemented price-support policy.

To rule out the possibility that the program is simply implemented better (or solely) in districts that are relatively more suitable for rice and wheat, I check whether the lack of effect holds for districts that have low relative suitability for rice but high absolute suitability, and find that they do[87]. Districts that are low in relative suitability allocate, on average, 40% of their cultivated land area to rice production, and, on average, dedicate more land to rice production than their highly relatively suitability counterparts. Relative suitability is therefore unlikely to be a mechanism for selection in implementing the program.

8.6 Responses in Program Implementation to Planting Decisions

It is also possible that program implementation at harvest responds to planting decisions after early-season rainfall is observed. The government might choose to increase procurement when a higher amount of rice and wheat has been planted in a particular district, for example. If this is unanticipated on the part of the farmer, then it should not enter into consideration at the time of planting. If consumers are aware that this is the case, then they are indeed responding to increased access to the program, since they might be aware that their probability of being able to sell to the government, should they want to, is higher. If anything,

[83] NSS 70

[84] This corresponds to agricultural seasons 2008-2009 to 2011-2012.

[85] The overall direction and magnitude of the results remain the same, with similar significance.

[86] For example, "Lackadaisical Govt Procurement Forces them to Sell Cheap", *The Hindu*, 07/09/2017

[87] Results available upon request

this overcomes the access constraints mentioned in the paragraph above, getting us closer to an accurate estimate of the effect of a well-implemented program on farmer decision-making.

8.7 Spillover Effects of Rice Cultivation on Wheat Cultivation

Rice cultivation begins in June, immediately after the southwest monsoon, while wheat cultivation occurs primarily in the *Rabi* season, which occurs from October through April. Given the staggered timing of rice and wheat production, there is a concern that rice production (and the resulting increase in income due to high rice support prices) drives the increase in wheat yields. To understand the effect of wheat support prices on farmers separately from the effects of rice support prices, I focus on the effect of wheat support prices on production in four subsamples of my data:

1. Years in which rice price supports are low relative to the rice price distribution - that is, the percentile of the support price relative to the price distribution is lower than the median across all years
2. Districts that plant over half their cultivated area with wheat in the *Rabi* season, but less than half of their cultivated area with rice in the *Kharif* season
3. The intersection of subsamples 1 and 2
4. Top-ten wheat-producing states, excluding Rajasthan and Madhya Pradesh

I present results in Table A1.7. I find results that are entirely consistent with my basic results with regard to area cultivated with wheat (no effect), total area cultivated (no effect), and significant increases in wheat yield, and in wheat production. This indicates that the influence of support price policies on wheat production are not driven by spillover responses in the *Rabi* season from the rice-intensive *Kharif* season.

Finally, I check if high rice support prices mitigate, rather than drive, the increases in wheat yields and production, and find that they do. In the final four columns of Table A1.7, I present results from a falsification test: I consider districts that devote more than half their *Kharif* season area share to rice, and less than half their *Rabi* season area share to wheat - these are districts that might rely relatively heavily on rice price supports and not on wheat price supports. I find no effect of high wheat support prices on production in those districts, suggesting that rice price supports can, in some instances, dampen the effects of the wheat pricing policy.

8.8 Individual States' Influence on Results

I exclude Rajasthan and Madhya Pradesh from all wheat specifications, even though they are significant contributors to wheat production in India. This is because they are states that have also had a long history of significant state-level bonuses to the national-level support price policy (Rs. 100-150 above the MSP in the years in my sample). I verify that patterns of response to the policy are unique for these two particular states, but hold entirely well across the board when they are excluded (Appendix Table A2.4). Given the influence of the state government on production patterns in these two states, I achieve a more characteristic estimate of the policy response by using the other 31 states alone.

I test that results are not driven by state-level policies or trends that encourage particular patterns of production, with the exception of Rajasthan and Madhya Pradesh for wheat. Since rainfall is also likely to be serially correlated within a state, it is particularly important that these state policies do not respond to early-season rainfall or rainfall predictions for the state and, in turn, influence my results. I therefore create leave-one-out estimators for each state for both rice and wheat cultivation, which are presented in Appendix

Tables A2.3 and A2.4. I find that my main results remain consistent in sign and magnitude and, in the vast majority of specifications, significant, across the state-level jackknife specifications.

9 Conclusion

This paper provides empirical evidence on producer responses to agricultural price supports, which can distort gains to farmers. I find that farmers respond in significant ways to price supports for two staples, rice and wheat, in the Indian Public Distribution System. Producers switch farmland into rice production, increasing output by 8% in response to good rainfall shocks in high-price-support years relative to years in which the price support is lower relative to the distribution of market prices. Wheat farmers, in contrast, do not change patterns of land cultivated, but similarly increase yield and total production significantly.

The production results, taken together, suggest that farmers are using more inputs per unit area cultivated for the two supported staple crops. Importantly, I find that the key source of increased agricultural yield is a reallocation of labor from the non-agricultural sector (particularly by contracted, rather than permanent, workers), resulting in a decrease in output of 8.5% in rural manufacturing and an increase in wages in the non-agricultural sector. This has, in line with other work by Gollin et al. (2013), Matsuyama (1992), Foster and Rosenzweig (2004, 2008), the potential to crowd-out growth driven by a more productive non-agricultural sector in favor of availing of these government incentives for agricultural production. The magnitudes of these effects are large: a measure of contract labor worker-days in manufacturing decreases by 17.8%, and gross output falls by 2.6% of a standard deviation. In addition, when the loss in manufacturing output is taken into account, the implicit cost of the price support program doubles.

Simultaneously, the increased use of less-efficient quantities of labor in the agricultural sector results in a decrease in agricultural productivity of 0.82 standard deviations. Agricultural price supports therefore hinder the growth of the non-agricultural sector, while reducing productivity in the agricultural sector they are meant to support.

Finally, from a policy perspective, price supports can, and do, place heavy administrative burdens on governments. At the same time, countries like India continue to battle high rates of malnutrition, stunting, and seasonal hunger. Recent estimates suggest that up to 10% of rice sold through the Public Distribution System rots and goes to waste. It is plausible that open market sales of rice (perhaps coupled with heavy consumer subsidies), lead to lower production but more effective distribution of food to poor households.

Future work can consider the specific labor market implications and broader welfare effects of price supports relative to direct lump-sum payments to farmers, or payments to farmers when agricultural productivity is low (insurance). Future work will also consider how to balance price policy and procurement across the entire spectrum of crops for which the government announces support prices to prevent wastage while still offering farmers income support when necessary.

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10 Tables

Table 1: Response of Wholesale Rice Prices to Early Season Rainfall, *Kharif* season

	Continuous Definition of Rainfall				Binary Definition of Rainfall		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
SAMPLE	If Pct Dev Early Season Rainfall≥0	If Pct Dev Early Season Rainfall<0	Full Sample	Full Sample	Full Sample	Full Sample	Full Sample
VARIABLES	Wholesale Px At Harvest	Wholesale Px At Harvest	1(Binding)	1(Binding)	Wholesale Px At Harvest	Wholesale Px At Harvest	Wholesale Px At Harvest
Pct Dev Early Season Rainfall From LR Avg	0.269	-0.879***		0.000509*			
	(0.273)	(0.294)		(.000299)			
1.(High Rice MSP)			0.0340**				
			(0.0140)				
Pct Dev Early Season...Avg * 1.(High Rice MSP)				-0.000490			
				(0.000444)			
1.(Good Early Rain)					-39.53***		-38.62**
					(11.69)		(15.88)
1.(Above Lowest Quintile Early Season Rainfall)						-26.13***	
						(8.850)	
1.(High Rice MSP)* 1.(Good Early Rain)							-24.83
							(15.12)
Observations	2,175	2,931	3,628	3,628	5,118	5,106	3,628
R-squared	0.705	0.789	0.486		0.722	0.722	0.745
Year FE	Yes	Yes	No	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses. Columns 1 and 2 show the response of rice wholesale prices to early-season productivity shocks for, respectively, the sample of districts with above-long-run-mean rainfall, and districts with below-long-run-mean rainfall. Columns 3 and 4 then provide a linear probability model that examines the first stage in the difference-in-difference strategy. Column 3 shows that the probability that the realized wholesale price binds (is lower than the support price) is higher in years defined as high price-support years. Column 3 does not include a year fixed effect, due to collinearity with the variable defining a given year as "high" or "low" price support. Column 4 shows that positive productivity shocks increase the probability that the support binds, in line with the decrease in price reflected in column 2, but that this is not significantly different in high and low support years. Then I move to my binary definition of productivity shocks, which I use in all tables that follow. Columns 5 and 6 show the responses of rice wholesale prices to two different (binary) definitions of positive productivity shocks. In Column 5, the productivity shock variable takes the value 1 if rainfall is above 50% below the long-run mean rainfall in that district. In Column 6, it takes the value 1 if rainfall is in the bottom quintile of the long-run rainfall distribution. Column 7 tests whether price responses to the rainfall shock defined in column 5 are significantly different in years defined as high and low price-support years, and provides support to Column 4 that this is not the case.

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Table 2: Agricultural Production, *Kharif* season

VARIABLES	(1) Rice Area Cultivated	(2) Rice Area Share	(3) Total Area Cultivated	(4) Rice Yield Per Unit Area	(5) Rice Production
1.(Good Early Rain)	-708.7	-0.0368***	4,219	-0.1184***	-20,615**
	(1,245)	(0.0109)	(2,967)	(0.0456)	(9,458)
1.(High Rice MSP)	3,342**	0.0397***	-2,715	0.1424***	18,682**
*1.(Good Early Rain)	(1,493)	(0.0135)	(3,441)	(0.0522)	(9,364)
Observations	3,608	3,608	3,608	3,608	3,608
R-squared	0.986	0.920	0.962	0.872	0.957
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes
Proportion Mean	0.0325	0.0657	-0.0126	0.0722	0.0853

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero rice production in the kharif season for all the years in the sample. Yield and production specifications also include cubic specifications of monthly rainfall in the post-planting period.

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Table 3: Crop Mix, *Kharif* season

VARIABLES	(1) Rice	(2) Other Cereals	(3) Pulses	(4) Oilseeds/Cash Crops	(5) Spices
1.(Good Early Rain)	-0.0368***	-0.00567	0.0108**	0.0129**	-0.0002
	(0.0109)	(0.0045)	(0.0052)	(0.0058)	(0.0002)
1.(High Rice MSP)*1.(Good Early Rain)	0.0397***	0.0169**	-0.0083	-0.0253***	0.000625**
	(0.0135)	(0.0084)	(0.0064)	(0.0071)	(0.0003)
Observations	3,608	3,608	3,608	3,608	3,608
R-squared	0.920	0.927	0.803	0.894	0.828
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes
Proportion Mean	0.0657	0.112	-0.119	-0.154	0.270

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero rice production in the kharif season for all the years in the sample. The crops included in each category are detailed in the Data Appendix.

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Table 4: Low Vs. High Relative Suitability (Rice), *Kharif* season

VARIABLES	(1) Full Total Area Cultivated	(2) High Total Area Cultivated	(3) Low Total Area Cultivated	(4) Full Rice Area	(5) High Rice Area	(6) Low Rice Area	(7) Full Rice Prop of Area Cultivated	(8) High Rice Prop of Area Cultivated	(9) Low Rice Prop of Area Cultivated
1.(Good Early Rain)	4,219	3,756	5,556	-708.7	-2,141	224.5	-0.0368***	-0.0539***	-0.0272*
	(2,967)	(3,960)	(4,682)	(1,245)	(1,593)	(1,982)	(0.0109)	(0.0148)	(0.0155)
1.(High Rice MSP)*	-2,715	-8,388*	735.9	3,342**	4,851**	1,472	0.0397***	0.0765***	0.0119
1.(Good Rain Kh)	(3,441)	(4,983)	(5,001)	(1,493)	(2,192)	(2,209)	(0.0135)	(0.0219)	(0.0163)
Observations	3,608	1,919	1,689	3,608	1,919	1,689	3,608	1,919	1,689
R-squared	0.962	0.944	0.966	0.986	0.975	0.990	0.920	0.909	0.920
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proportion Mean	-0.0126	-0.0514	0.00270	0.0325	0.0530	0.0127	0.0657	0.109	0.0240

VARIABLES	(10) Full Rice Yield	(11) High Rice Yield	(12) Low Rice Yield	(13) Full Production of Rice	(14) High Production of Rice	(15) Low Production of Rice
1.(Good Early Rain)	-0.0796*	-0.0900	-0.0906	-13,893	-8,951	-20,347
	(0.0454)	(0.0600)	(0.0667)	(9,543)	(7,149)	(16,992)
1.(High Rice MSP)*	0.116**	0.174**	0.0907	14,919	16,935**	14,689
1.(Good Rain Kh)	(0.0534)	(0.0784)	(0.0745)	(9,626)	(8,355)	(16,638)
Observations	3,608	1,919	1,689	3,608	1,919	1,689
R-squared	0.872	0.878	0.875	0.956	0.964	0.952
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Proportion Mean	0.0593	0.0895	0.0465	0.0689	0.0856	0.0617

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero rice production in the kharif season for all the years in the sample. Yield and production specifications also include a cubic polynomial of monthly rainfall during the post-planting cultivation season. 'High' refers to districts with above-median suitability for rice, and 'low' to districts with below-median suitability for rice.

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Table 5: Monthly Per Capita Expenditure, *Kharif* season

	(1) Rice Households Trimmed	(2) Rice Households Winzorized	(3) Non-Rice Households Trimmed	(4) Non-Rice Households Winzorized
VARIABLES	Log(MPCE)	Log(MPCE)	Log(MPCE)	Log(MPCE)
1.(Good Early Rain)	0.00950	-0.00266	4.09e-05	-0.00313
	(0.0145)	(0.0148)	(0.0135)	(0.0140)
1.(High Rice MSP)	0.0589***	0.0518***	0.0205	0.0145
	(0.0167)	(0.0169)	(0.0164)	(0.0170)
1.(High Rice MSP)*	-0.0182	-0.0120	0.00863	0.0161
1.(Good Early Rain)	(0.0178)	(0.0181)	(0.0167)	(0.0177)
Constant	6.718***	6.823***	6.783***	6.840***
	(0.117)	(0.127)	(0.0790)	(0.0808)
Observations	37,652	38,034	71,321	72,037
R-squared	0.454	0.465	0.402	0.410
Early Rainfall in Prediction	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No
Rainfall	Yes	Yes	Yes	Yes
HH Char	Yes	Yes	Yes	Yes
Year FE	No	No	No	No
District FE	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Standard errors clustered at the district-year level. This analysis excludes all districts that have zero rice production in the kharif season for all the years in the sample. I include only rural households that are surveyed in the harvest season and report consumption of home-produced rice (as rice households). Non-rice households are included if they produce at least one agricultural good. Household characteristics controlled for include religion, household type, household size, social group, and land possessed. All specifications also control for a cubic polynomial of monthly post-planting rainfall. Columns 1 and 3: I exclude the top 1% of per-capita expenditure observations. Columns 2 and 4: Per-capita expenditure is winzorized to the 99th percentile.

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Table 6: Labor Market Responses to Price Supports, *Kharif* season

	Agriculture			**Non-Agriculture**			**Non-Agriculture ASI Data**		
VARIABLES	(1) 1.(Main Activity Agri)	(2) Agri Days (of past week)	(3) Agri Wage	(4) 1.(Main Activity Non-Agri)	(5) Non-Agri Days (of past week)	(6) NonAgri Wage	(7) Total Days	(8) Contract Days	(9) Non-Contract Days
1.(Good Early Rain)	-0.0641**	-0.448**	10.34**	0.0783***	0.548***	-25.07**	1,331	1,481	503.9
	(0.0273)	(0.191)	(4.88)	(0.0248)	(0.173)	(12.51)	(1,870)	(2,413)	(1,226)
1.(High Rice MSP)*	0.0735**	0.512**	-9.91**	-0.0800***	-0.561***	30.56**	-4,560**	-5,617**	-1,609
1.(Good Early Rain)	(0.0294)	(0.205)	(4.91)	(0.0265)	(0.185)	(13.90)	(2,155)	(2,738)	(1,205)
Observations	72,614	72,619	16,261	72,614	72,619	13,867	98,774	36,791	88,713
R-squared	0.251	0.250	0.514	0.228	0.228	0.442	0.191	0.166	0.188
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proportion Mean	0.0982	0.0978	-0.206	-0.357	-0.358	0.230	-0.0940	-0.178	-0.0525

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero rice production in the kharif season for all the years in the sample. Columns 1-6 consider labor market outcomes from the NSS household survey of employment. I include only agricultural households in the rural sample that are surveyed in the kharif cultivation season, and individuals who have indicated they have worked or searched for work in the past week. Standard individual and household controls - household size, household type, land possessed, social group, age, sex, education, religion and marital status- are included in all specifications. I also include cubic polynomials of monthly rainfall throughout the cultivation period. Wage regressions are restricted to individuals with non-zero wages. Columns 7-9 consider labor use in firms (both formal and informal) in the Annual Survey of Industries data. Column (7) considers total manufacturing days, while columns (8) and (9) consider permanent and contracted workers separately. The ASI analysis includes only open firms operating in the rural sector. It also includes a vector of firm-level controls, including industry, ownership, age, age squared, organization type, and number of plants.

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Table 7: Occupation Choice, *Kharif* season

VARIABLES	(1) Manufacturing 1.(Worked Manufacturing)	(2) Construction 1.(Worked Construction)
1.(Good Early Rain)	0.0191*	0.0128**
	(0.0104)	(0.0060)
1.(High Rice MSP)*1.(Good Early Rain)	-0.0228**	-0.0153**
	(0.0107)	(0.0064)
Observations	73,701	73,701
R-squared	0.381	0.051
Year FE	Yes	Yes
District FE	Yes	Yes
State x Time Trends	Yes	Yes
Proportion Mean	-0.300	-0.644

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Standard errors clustered at the district level. This analysis excludes all districts that have zero rice production in the kharif season for all the years in the sample. I include only agricultural households in the rural sample that are surveyed in the kharif cultivation season, and individuals who have indicated they have worked or searched for work in the past week. Standard individual and household controls - household size, household type, land possessed, social group, age, sex, education, religion and marital status- are included in all specifications. I also include cubic polynomials of monthly rainfall throughout the cultivation period.

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Table 8: Other Inputs, *Kharif* season

VARIABLES	(1) Proportion of Rice Area Irrigated	(2) Quant Fert Per Unit Area	(3) Proportion of Rice Area HYV
1.(Good Early Rain)	1.642*	-1.013	0.392
	(0.899)	(0.810)	(1.014)
Percentile of MSP*1.(Good Early Rain)	-0.0393*	0.0285	-0.0080
	(0.0223)	(0.0211)	(0.0249)
Observations	740	765	740
R-squared	0.904	0.959	0.928
Year FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes
Proportion Mean	-0.0543	0.0573	-0.0121

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero rice production in the kharif season for all the years in the sample. "Percentile of MSP" refers to the percentile of the support price in the predicted price distribution for the year.

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Table 9: Non-Agricultural Ouptut and Agricultural Productivity

	Non-Agricultural Output		Agricultural Productivity
	(1)	(2)	(3)
VARIABLES	Gross Output	Value-added	T-T Index
Good Early Rain	9.196e+07**	6.219e+07	0.6716***
	(4.462e+07)	(4.306e+07)	(0.2541
1.(High Rice MSP)*1.(Good Early Rain)	-1.791e+08***	-6.250e+07	-0.9209***
	(6.174e+07)	(5.469e+07)	(0.2998)
Constant	2.775e+08	-2.058e+08	-1.550*
	(5.707e+08)	(3.951e+08)	(0.9295)
Observations	83,895	83,895	1,281
R-squared	0.067	0.038	0.376
Early Rainfall in Prediction	Yes	Yes	Yes
MSP in Prediction	No	No	No
Rainfall	Yes	Yes	Yes
Year FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes
Firm Char	Yes	Yes	
Proportion SD	-0.0263	-0.0126	-0.822

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. Analysis on non-agricultural firms uses the ASI data, and includes only open firms operating in the rural sector. It also includes a vector of firm-level controls, including industry, ownership, age, age squared, organization type, and number of plants. Value-added is defined as total gross output minus total gross domestic inputs. In Column 3, I present results from my agricultural productivity analysis using the Tornqvist-Theil index. Details are provided in Appendix 4.2. All specifications include a cubic polynomial of rainfall in the cultivation period. In this table, I present results as a proportion of the standard deviation of the outcome variable, rather than its mean, due to the number of zero and negative observations in the value-added variable and in the Tornqvist-Theil index.

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Table 10: Response of Wheat Prices to Early Season Rainfall, *Rabi* season

	(1)	(2)	(3)	(4)	(5)
SAMPLE	If Pct Dev Early Season Rainfall≥0	If Pct Dev Early Season Rainfall<0	Full Sample	Full Sample	Full Sample
VARIABLES	Wholesale Price At Harvest	Wholesale Price At Harvest	Wholesale Price At Harvest	Wholesale Price At Harvest	Wholesale Price At Harvest
Pct Dev Early Season Rainfall	-0.0492	-0.321***			
From LR Avg	(0.0636)	(0.107)			
1.(Good Early Rain)			-25.68***		-39.37***
			(6.540)		(11.09)
1.(Above Lowest Quintile of				-15.78***	
Early Season Rainfall)				(4.564)	
1.(High Wheat MSP)*					10.88
1.(Good Early Rain)					(18.05)
Constant	527.6***	525.6***	542.7***	531.0***	677.9***
	(12.62)	(13.43)	(8.743)	(8.033)	(16.54)
Observations	2,231	2,464	4,707	4,695	3,293
R-squared	0.921	0.901	0.904	0.904	0.897
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses.

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Table 11: Agricultural Production, *Rabi* season

VARIABLES	(1) Wheat Area Cultivated	(2) Wheat Area Share	(3) Total Area Cultivated	(4) Wheat Yield Per Unit Area	(5) Wheat Production
1.(Good Early Rain)	3,181**	-0.00806	6,591**	-0.0498	-4,009
	(1,228)	(0.00827)	(2,813)	(0.0289)	(4,936)
1.(High Rice MSP)*	354.5	0.0232*	-10,163	0.169***	25,138***
*1.(Good Early Rain)	(2,134)	(0.0137)	(5,389)	(0.0567)	(8,231)
Observations	2,598	2,598	2,598	2,598	2,598
R-squared	0.9364	0.875	0.960	0.936	0.988
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes
Proportion Mean	0.0800	0.0397	-0.0731	0.0800	0.0973

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero wheat production in the rabi season for all the years in the sample, and all districts in the states of Rajasthan and Madhya Pradesh. Yield and production specifications also include cubic specifications of monthly rainfall in the post-planting period.

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Table 12: Low Vs. High Relative Suitability (Wheat)

VARIABLES	(1) Full Total Area Cultivated	(2) High Total Area Cultivated	(3) Low Total Area Cultivated	(4) Full Wheat Area	(5) High Wheat Area	(6) Low Wheat Area	(7) Full Wheat Prop of Area Cultivated	(8) High Wheat Prop of Area Cultivated	(9) Low Wheat Prop of Area Cultivated
1.(Good Early Rain)	6,690**	-4,138***	11,919***	3,865***	-1,117	7,110***	-0.0284**	-0.0503***	-0.00801
	(2,830)	(1,366)	(4,378)	(1,380)	(816.1)	(2,016)	(0.0111)	(0.0188)	(0.0127)
1.(High Wheat MSP)*	-6,675	7.352	-17,149	3,990	-392.0	3,176	0.0528***	0.0718*	0.0142
1.(Good Rain Rb)	(7,943)	(1,694)	(13,781)	(2,643)	(1,137)	(4,442)	(0.0192)	(0.0425)	(0.0247)
Observations	2,598	1,281	1,317	2,598	1,281	1,317	2,598	1,281	1,317
R-squared	0.958	0.982	0.946	0.988	0.992	0.986	0.809	0.777	0.837
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proportion Mean	-0.0480	8.25e-05	-0.0914	0.0478	-0.00578	0.0322	0.0903	0.113	0.0267

VARIABLES	(10) Full Wheat Yield	(11) High Wheat Yield	(12) Low Wheat Yield	(13) Full Production of Wheat	(14) High Production of Wheat	(15) Low Production of Wheat
1.(Good Early Rain)	-0.0259	-0.0605	0.0126	9,536*	-1,938	18,505***
	(0.0363)	(0.0755)	(0.0309)	(5,304)	(5,996)	(7,051)
1.(High Wheat MSP)*	0.187***	0.228***	0.0973	10,703	1,329	3,367
1.(Good Rain Rb)	(0.0552)	(0.0791)	(0.0725)	(10,695)	(8,759)	(17,628)
Observations	2,598	1,281	1,317	2,598	1,281	1,317
R-squared	0.907	0.873	0.945	0.982	0.989	0.979
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Proportion Mean	0.0883	0.110	0.0450	0.0412	0.00618	0.0111

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero wheat production in the Rabi season for all the years in the sample,and all districts in the states of Rajasthan and Madhya Pradesh. Yield and production specifications also include cubic specifications of monthly rainfall in the post-planting period.'High' refers to districts with above-median suitability for wheat, and 'low' to districts with below-median suitability for wheat .

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Table 13: Monthly Per Capita Expenditure at Harvest, *Rabi* season

VARIABLES	(1) Wheat Households Winzorized	(2) Non-Wheat Households Winzorized
1.(Good Early Rain)	-65.86*	-10.59
	(34.79)	(40.61)
1.(High Wheat MSP)*1.(Good Early Rain)	72.17	-82.65
	(57.45)	(75.43)
Constant	909.6***	918.1***
	(111.3)	(173.1)
Observations	20,698	58,728
R-squared	0.533	0.256
Early Rainfall in Prediction	Yes	Yes
MSP in Prediction	No	No
Rainfall	Yes	Yes
HH Char	Yes	Yes
Year FE	Yes	Yes
District FE	Yes	Yes
State x Time Trends	Yes	Yes
Proportion Mean	0.0662	-0.0813

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero wheat production in the rabi season for all the years in the sample, and all households in the states of Rajasthan and Madhya Pradesh. I include only rural households that are surveyed in the harvest season and report consumption of home-produced wheat (as wheat households). Non-wheat households are included if they produce at least one agricultural good. Household characteristics controlled for include religion, household type, household size, social group, and land possessed. All specifications also control for a cubic polynomial of monthly post-planting rainfall. Per-capita expenditure is winzorized to the 99th percentile.

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Table 14: Labor Market Responses to Price Supports, *Rabi* season

	Agriculture			**Non-Agriculture**		
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	1.(Main Activity Agri)	Agri Days	Agri Wage	1.(Main Activity Non-Agri)	Non-Agri Days	NonAgri
1.(Good Early Rain)	-0.00814	-0.0555	7.230	0.0101	0.0785	-8.643
	(0.0146)	(0.102)	(5.13)	(0.0141)	(0.0984)	(7.820)
1.(High Wheat MSP)*	0.0310	0.261*	-11.93	-0.0463**	-0.269**	6.095
1.(Good Early Rain)	(0.0202)	(0.141)	(8.18)	(0.0195)	(0.136)	(12.86)
Observations	40,453	40,455	8,681	40,453	40,455	10,771
R-squared	0.267	0.267	0.144	0.247	0.248	0.456
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Proportion Mean	0.0407	0.0488	-0.212	-0.224	-0.186	0.0446

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero wheat production in the rabi season for all the years in the sample, and all households in the states of Rajasthan and Madhya Pradesh. I include only agricultural households in the rural sample that are surveyed in the rabi cultivation season, and individuals who have indicated they have worked or searched for work in the past week. Standard individual and household controls - household size, household type, land possessed, social group, age, sex, education, religion and marital status- are included in all specifications. I also include cubic polynomials of monthly rainfall throughout the cultivation period.

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A1 Robustness Checks

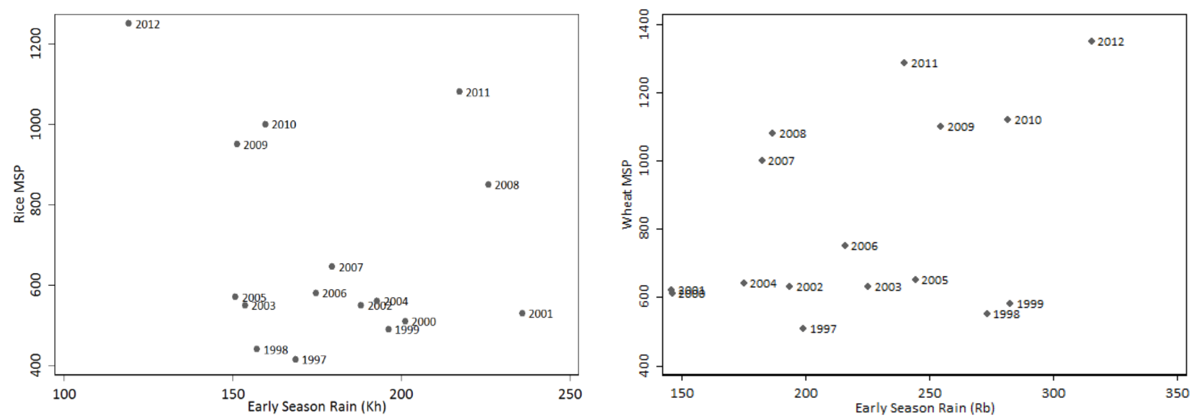

Figure A1.1: MSPs for rice (*Kharif* season) and wheat (*Rabi* season) plotted against early-season rainfall across the country between 1997 and 2012.
Note: Early-season rainfall is weighted by area cultivated in that season in a given district. Year t refers to the planting season t,t+1. For example, 2012 refers to the 2012-2013 season.

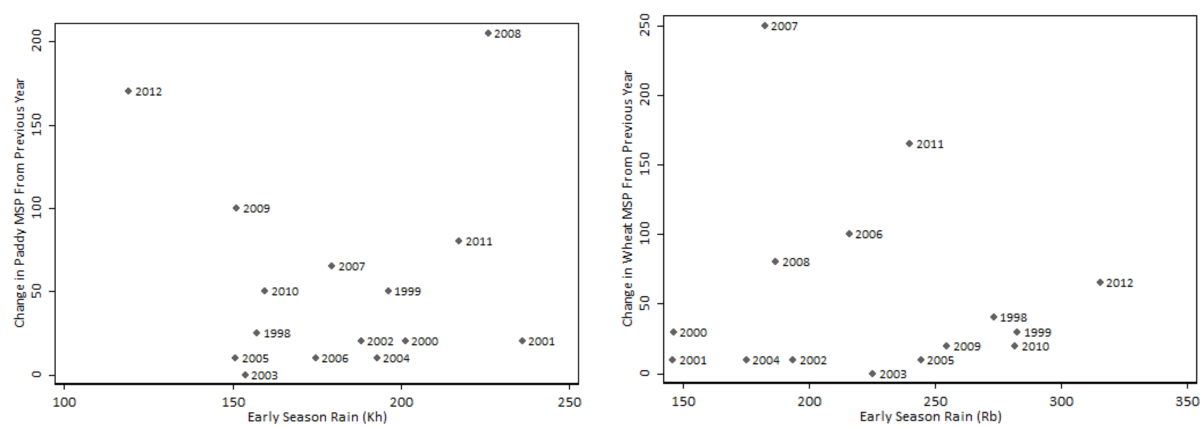

Figure A1.2: Change in MSPs for rice (*Kharif* season) and wheat (*Rabi* season) plotted against early-season rainfall across the country between 1997 and 2012.
Note: Early-season rainfall is weighted by area cultivated in that season in a given district. Year t refers to the planting season t,t+1. For example, 2012 refers to the 2012-2013 season.

[Regression Tests of Aggregate Rainfall and Price Supports: Table A1.1]

Table A1.1: Response of MSP to Various Potential Factors

PANEL A: Response of MSP to Early-Season Rainfall

VARIABLES	(1) Real Paddy MSP	(2) Change in Real Paddy MSP	(3) Real Wheat MSP	(4)) Change in Real Wheat MSP
Early Season Rain	0.261	0.564	0.512	-0.324
	(0.936)	(0.438)	(0.580)	(0.363)
Year Trend	10.81***	3.627	53.88***	7.598*
	(4.314)	(3.929)	(6.166)	(4.219)
Observations	16	15	16	15
R-squared	0.276	0.445	0.417	0.007

PANEL B: Response of MSP to Monsoon Forecasts

VARIABLES	(1) Real Paddy MSP	(2) Change in Real Paddy MSP	(3) Real Wheat MSP	(4)) Change in Real Wheat MSP
Num Days	0.261	0.564	0.512	-0.324
	(0.936)	(0.438)	(0.580)	(0.363)
Year Trend	10.81***	3.627	53.88***	7.598*
	(4.314)	(3.929)	(6.166)	(4.219)
Observations	16	15	16	15
R-squared	0.835	0.403	0.879	0.218

*** p<0.01, ** p<0.05, * p<0.1

Robust standard errors in parentheses. Early-season rainfall is weighted by area cultivated in that season in a given district. Monsoon forecasts in Panel B (num days) are defined as the number of days after the normal onset date that the monsoon is predicted to arrive (negative for early arrival).

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Table A1.2: Staple Production Response to Alternate Definition of Good Rain

PANEL A: Alternate Definition of Good Rain, *Kharif* season

VARIABLES	(1) Total Area Cultivated	(2) Rice Area	(3) Rice Proportion of Area Cultivated	(4) Rice Yield	(5) Production of Rice
1.(Above Lowest Quintile of Early Rainfall)	2,588	-400.8	-0.0304***	-0.0117	-6,336
	(2,564)	(1,244)	(0.00883)	(0.0406)	(7,702)
1.(Above lowest quintile...)* 1.(High Rice MSP)	-4,387	2,636**	0.0425***	0.0574	10,267
	(3,246)	(1,271)	(0.0114)	(0.0465)	(7,840)
Constant	351,784***	1,068	0.139***	1.448***	-78,719
	(24,173)	(14,747)	(0.0338)	(0.199)	(54,006)
Observations	3,597	3,597	3,597	3,597	3,597
R-squared	0.962	0.986	0.920	0.871	0.956
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes
Proportion Mean	-0.0204	0.0257	0.0703	0.0295	0.0475

PANEL B: Alternate Definition of Good Rain, *Rabi* season

VARIABLES	(1) Total Area Cultivated	(2) Wheat Area	(3) Wheat Proportion of Area Cultivated	(4) Wheat Yield	(5) Production of Wheat
1.(Above Lowest Quintile of Early Season Rainfall)	4,394**	3,643***	0.00843	-0.00377	5,534
	(2,007)	(1,063)	(0.00727)	(0.0213)	(3,394)
1.(Above lowest quintile...)* 1.(High Wheat MSP)	-9,138**	565.1	0.0152	0.150***	17,909***
	(4,296)	(1,562)	(0.0117)	(0.0369)	(5,231)
Constant	58,602*	-11,108*	-0.300***	1.227***	33,031*
	(31,325)	(6,107)	(0.0860)	(0.292)	(17,889)
Observations	2,587	2,587	2,587	2,587	2,587
R-squared	0.960	0.989	0.875	0.935	0.987
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes
Proportion Mean	-0.0656	0.00675	0.0260	0.0706	0.0688

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero rice production in the kharif season (Panel A) or zero wheat production in the rabi season (Panel B) for all the years in the sample. Good rain is defined as rain in the 2nd through 5th quintiles of rainfall deviation from the long-run average. Panel B excludes all districts in the states of Madhya Pradesh and Rajasthan.

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Table A1.3: Rice Cultivation Responses using Various Predictions (*Kharif* season)

PANEL A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Rice Area	Rice Area	Rice Area	Total Area	Total Area	Total Area	Rice Area Share	Rice Area Share	Rice Area Share
1.(Good Early Rain)	-650.3	-708.7	-2,559**	3,022	4,219	460.2	-0.0327***	-0.0368***	-0.0351***
	(1,403)	(1,245)	(1,172)	(3,215)	(2,967)	(2,728)	(0.0102)	(0.0109)	(0.0127)
1.(High Rice MSP)	4,099**	3,342**	6,002***	-789.7	-2,715	3,513	0.0412***	0.0397***	0.0335**
*1.(Good Early Rain)	(1,709)	(1,493)	(1,588)	(4,097)	(3,441)	(3,823)	(0.0155)	(0.0135)	(0.0149)
R-squared	0.986	0.986	0.986	0.962	0.962	0.962	0.920	0.920	0.920
Proportion Mean	0.0398	0.0325	0.0583	-0.00368	-0.0126	0.0164	0.0682	0.0657	0.0555
PANEL B	(10)	(11)	(12)	(13)	(14)	(15)			
VARIABLES	Rice Yield	Rice Yield	Rice Yield	Rice Production	Rice Production	Rice Production			
1.(Good Early Rain)	-0.199***	-0.180***	-0.202***	-29,099***	-26,733***	-28,565***			
	(0.0427)	(0.0489)	(0.0512)	(9,565)	(9,911)	(10,800)			
1.(High Rice MSP)*	0.219***	0.140***	0.158***	28,613***	18,446**	19,224*			
1.(Good Early Rain)	(0.0521)	(0.0527)	(0.0548)	(9,101)	(9,220)	(9,989)			
R-squared	0.8785	0.8778	0.8779	0.9573	0.9572	0.9572			
Proportion Mean	0.113	0.0718	0.0814	0.132	0.0853	0.0889			
Observations	3,608	3,608	3,608	3,608	3,608	3,608	3,608	3,608	3,608
Early Rainfall in Prediction	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
MSP in Prediction	No	No	Yes	No	No	Yes	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero rice production in the kharif season for all the years in the sample. Yield and production specifications also include cubic specifications of monthly rainfall in the post-planting period.

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Table A1.4: Wheat Cultivation Responses using Various Predictions (*Rabi* season)

PANEL A	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
VARIABLES	Wheat Area	Wheat Area	Wheat Area	Total Area	Total Area	Total Area	Wheat Area Share	Wheat Area Share	Wheat Area Share
1.(Good Early Rain)	3,578***	3,181**	2,518**	6,853**	6,591**	4,843**	-0.00355	-0.00806	-0.00725
	(1,316)	(1,228)	(1,164)	(3,041)	(2,813)	(2,228)	(0.00758)	(0.00827)	(0.00881)
1.(High Rice MSP)	-756.0	354.5	2,946	-7,762	-10,163	-4,092	0.00479	0.0232*	0.0216
*1.(Good Early Rain)	(1,685)	(2,134)	(2,983)	(5,389)	(7,361)	(6,622)	(0.0129)	(0.0137)	(0.0168)
R-squared	0.989	0.989	0.989	0.960	0.960	0.960	0.875	0.875	0.875
Proportion Mean	-0.00905	0.00425	0.0353	-0.0558	-0.0731	-0.0294	0.00818	0.0397	0.0370
PANEL B	(10)	(11)	(12)	(13)	(14)	(15)			
VARIABLES	Wheat Yield	Wheat Yield	Wheat Yield	Wheat Production	Wheat Production	Wheat Production			
1.(Good Early Rain)	-0.0704**	-0.0498	0-.0293	30.47	-4,009	-5,627			
	(0.0277)	(0.0289)	(0.0281)	(5,497)	(4,936)	(5,054)			
1.(High Rice MSP)*	0.167***	0.169***	0.110*	7,444	25,138***	33,091***			
1.(Good Early Rain)	(0.0560)	(0.0567)	(0.0607)	(7,357)	(8,231)	(9,063)			
R-squared	0.9364	0.9364	0.9367	0.9877	0.9878	0.9878			
Proportion Mean	0.0788	0.0800	0.0519	0.0288	0.0973	0.1281			
Observations	2,598	2,598	2,598	2,598	2,598	2,598	2,598	2,598	2,598
Early Rainfall in Prediction	No	Yes	Yes	No	Yes	Yes	No	Yes	Yes
MSP in Prediction	No	No	Yes	No	No	Yes	No	No	Yes
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero wheat production in the rabi season for all the years in the sample, and districts in the states of Rajasthan and Madhya Pradesh. Yield and production specifications also include cubic specifications of monthly rainfall in the post-planting period.

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Table A1.5: Rice Yield Reponses by Size of the Farmers' Information Set, *Kharif* season

	(1) Three-Year Recall	(2) Five-Year Recall	(3) Seven-Year Recall
VARIABLES	Rice Yield	Rice Yield	Rice Yield
1.(Good Early Rain)	-0.1330***	-0.1184***	-0.1969***
	(0.0434)	(0.0456)	(0.0589)
1.(High Rice MSP)*1.(Good Early Rain)	0.0953*	0.1424***	0.1979***
	(0.0535)	(0.0522)	(0.0633)
Observations	4,180	3,608	2,904
R-squared	0.875	0.872	0.881
Year FE	Yes	Yes	Yes
District FE	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes
Proportion Mean	0.0486	0.0722	0.0983

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero rice production in the kharif season for all the years in the sample. Specifications include controls for a cubic polynomial of post-planting rainfall.

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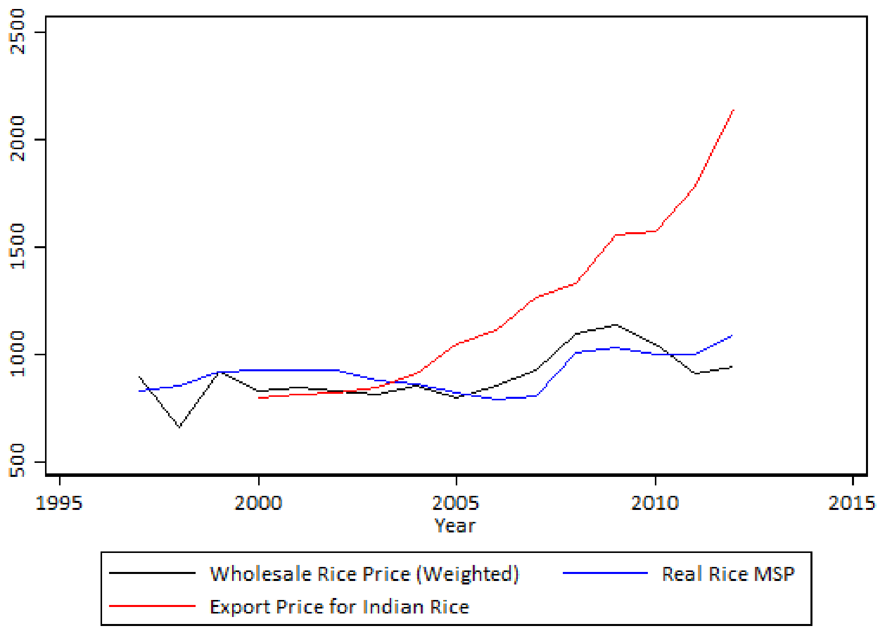

Figure A1.3: Variation over time in real MSP, weighted mean real price, and real export price of common rice from India

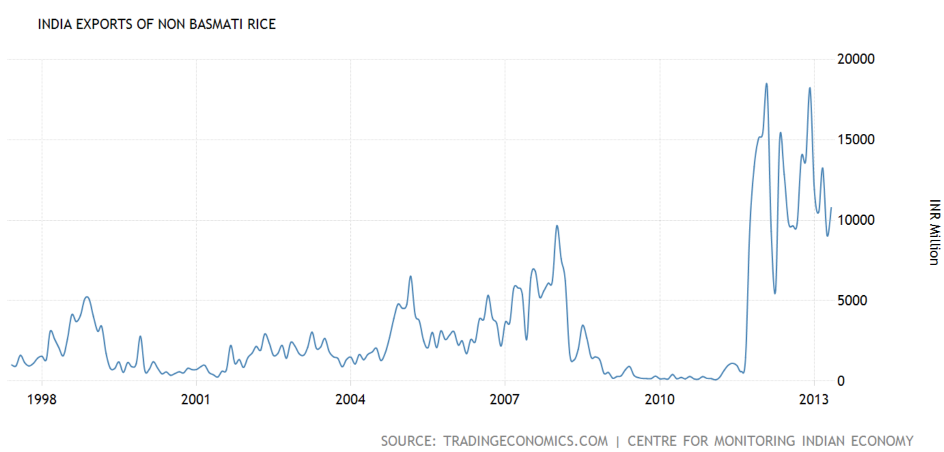

Figure A1.4: Amount of common rice exported from India

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Table A1.6: Staple Production During Export Bans

PANEL A: Rice Production During Export Ban (2008-2011), *Kharif* season

VARIABLES	(1) Total Area Cultivated	(2) Rice Area	(3) Rice Proportion of Area Cultivated	(4) Rice Yield	(5) Production of Rice
1.(Good Early Rain)	5,964	-3,527**	-0.0566***	-0.0540	-7,828
	(4,266)	(1,672)	(0.0181)	(0.0448)	(9,333)
1.(High Rice MSP)*	-9,182	6,373**	0.0463	0.126	12,187
1.(Good Rain Kh)	(6,275)	(2,649)	(0.0286)	(0.0889)	(11,558)
Constant	94,524	-159,103***	0.216**	3.577***	-298,346*
	(60,033)	(40,774)	(0.0981)	(0.855)	(170,340)
Observations	1,353	1,353	1,353	1,353	1,353
R-squared	0.972	0.990	0.924	0.927	0.968
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes
Proportion Mean	-0.0427	0.0623	0.0756	0.0640	0.0546

PANEL B: Wheat Production During Export Ban (2007-2009), *Rabi* season

VARIABLES	(1) Total Area Cultivated	(2) Wheat Area	(3) Wheat Proportion of Area Cultivated	(4) Wheat Yield	(5) Production of Wheat
1.(Good Early Rain)	8,656*	4,771	-0.0270	-0.0126	10,138
	(4,761)	(3,937)	(0.0183)	(0.0789)	(13,036)
1.(High Wheat MSP)*	2,003	199.4	-0.0121	0.259***	16,666
1.(Good Early Rain)	(5,240)	(4,201)	(0.0315)	(0.0961)	(16,048)
Constant	78,994***	-1,657	0.0555**	1.083***	-11,094
	(5,655)	(4,319)	(0.0226)	(0.0863)	(14,213)
Observations	757	757	757	757	757
R-squared	0.987	0.995	0.901	0.935	0.994
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes
Proportion Mean	0.0154	0.00247	-0.0201	0.125	0.0662

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero rice production in the kharif season (Panel A) or districts that have zero wheat production in the rabi season and all districts in the states of Rajasthan and Madhya Pradesh (Panel B) for all the years in the sample. Specifications for yield and production include a cubic polynomial of monthly post-planting precipitation during the cultivation period.

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Table A1.7: Tests on Various Subsamples of Wheat-Producing Districts

VARIABLES	(1) Test1a Wheat Area	(2) Test1b Total Area Cultivated	(3) Test1c Wheat Yield	(4) Test1d Production of Wheat	(5) Test2a Wheat Area	(6) Test2b Total Area Cultivated	(7) Test2c Wheat Yield	(8) Test2d Production of Wheat	(9) Test3a Wheat Area	(10) Test3b Total Area Cultivated	(11) Test3c Wheat Yield	(12) Test3d Production Wheat
1.(Good Early Rain)	576.2	1,021	-0.0793**	-8,774*	6,143**	2,290	-0.138***	5,743	1,392	-1,127	-0.133*	-18,195
	(994.6)	(2,465)	(0.0323)	(4,687)	(2,509)	(3,042)	(0.0499)	(8,616)	(3,455)	(5,322)	(0.0778)	(16,531)
1.(High Wheat MSP)*	3,148	7,036	0.240***	34,140***	-614.3	-1,425	0.361***	23,097	81.64	-4,269	0.307**	31,569
1.(Good Rain Rb)	(2,708)	(6,801)	(0.0548)	(11,590)	(3,274)	(4,488)	(0.0996)	(14,248)	(4,905)	(7,975)	(0.122)	(25,225)
Observations	1,403	1,403	1,403	1,403	522	522	522	522	279	279	279	279
R-squared	0.990	0.977	0.942	0.987	0.986	0.987	0.954	0.981	0.990	0.992	0.964	0.985
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

VARIABLES	(13) Test4a Wheat Area	(14) Test4b Total Area Cultivated	(15) Test4c Wheat Yield	(16) Test4d Production of Wheat	(17) Test5a Wheat Area	(18) Test5b Total Area Cultivated	(19) Test5c Wheat Yield	(20) Test5d Production of Wheat
1.(Good Early Rain)	3,986***	8,629**	-0.0201	5,147	-388.7	-5,729	0.0637	-1,202
	(1,497)	(3,460)	(0.0253)	(5,204)	(2,003)	(3,569)	(0.0741)	(9,699)
1.(High Wheat MSP)*	964.3	-10,677	0.225***	26,157***	-1,053	-1,593	-0.00319	10,848
1.(Good Rain Rb)	(2,529)	(8,792)	(0.0519)	(9,827)	(4,102)	(5,554)	(0.132)	(19,304)
Observations	1,773	1,773	1,773	1,773	658	658	658	658
R-squared	0.987	0.943	0.929	0.985	0.997	0.991	0.954	0.994
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero wheat production in the rabi season for all the years in the sample. Test 1: Restricting to years in which the rice price floor is low. Test 2: Restricting to districts in which the proportion of area cultivated with rice is less than 50% in the Kharif season and proportion of area cultivated with wheat in the rabi season is more than 50%. Test 3: Identical to test 2, but restricted to years in which the rice price floor is low. Test 4: Restricted to top 8 wheat producing states, excluding Madhya Pradesh and Rajasthan. Test 5: A falsification test that restricts analysis to years in which the paddy support price is high and to districts in which the proportion of area cultivated with rice in the Kharif season is greater than 50%. For test 5 alone, we observe no significant effect on wheat cultivation from the wheat support price, presumably due to a spillover effect from the Kharif season.

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A2 Additional Tables

Table A2.1: Low Vs. High Prices (Rice)

VARIABLES	(1) Full Total Area Cultivated	(2) High Total Area Cultivated	(3) Low Total Area Cultivated	(4) Full Rice Area	(5) High Rice Area	(6) Low Rice Area	(7) Full Rice Prop of Area Cultivated	(8) High Rice Prop of Area Cultivated	(9) Low Rice Prop of Area Cultivated
1.(Good Early Rain)	4,219	2,957	19,487**	-708.7	-763.9	2,354	-0.0368***	-0.0295**	-0.0963***
	(2,967)	(3,926)	(8,526)	(1,245)	(1,477)	(3,603)	(0.0109)	(0.0125)	(0.0313)
1.(High Rice MSP)*	-2,715	-4,804	-12,881	3,342**	1,237	4,663	0.0397***	0.0228	0.110***
1.(Good Early Rain)	(3,441)	(4,788)	(9,423)	(1,493)	(1,931)	(4,280)	(0.0135)	(0.0153)	(0.0409)
Observations	3,608	2,533	1,075	3,608	2,533	1,075	3,608	2,533	1,075
R-squared	0.962	0.967	0.967	0.986	0.990	0.977	0.920	0.940	0.923
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proportion Mean	-0.0126	-0.0215	-0.0665	0.0325	0.0117	0.0485	0.0657	0.0394	0.165

VARIABLES	(10) Full Rice Yield	(11) High Rice Yield	(12) Low Rice Yield	(13) Full Production of Rice	(14) High Production of Rice	(15) Low Production of Rice
1.(Good Early Rain)	-0.0796*	-0.0228	-0.434***	-13,893	-9,308	-38,878*
	(0.0454)	(0.0468)	(0.147)	(9,543)	(10,372)	(22,820)
1.(High Rice MSP)*	0.116**	0.0563	0.452***	14,919	6,442	44,561**
1.(Good Rain Kh)	(0.0534)	(0.0581)	(0.156)	(9,626)	(11,415)	(21,278)
Observations	3,608	2,533	1,075	3,608	2,533	1,075
R-squared	0.872	0.889	0.878	0.956	0.960	0.956
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Proportion Mean	0.0593	0.0274	0.266	0.0689	0.0276	0.253

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. This analysis excludes all districts that have zero rice production in the kharif season for all the years in the sample. Yield and production specifications also include a cubic polynomial of monthly rainfall during the post-planting cultivation season.

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Table A2.2: Low Vs. High Prices (Wheat)

VARIABLES	(1) Full Total Area Cultivated	(2) High Total Area Cultivated	(3) Low Total Area Cultivated	(4) Full Wheat Area	(5) High Wheat Area	(6) Low Wheat Area	(7) Full Wheat Proportion of Area Cultivated	(8) High Wheat Proportion of Area Cultivated	(9) Low Wheat Proportion of Area Cultivated
Good Early Rain Rabi	6,690**	10,098***	-2,119	3,865***	4,597***	2,856	-0.0284**	-0.0301**	-0.0515
	(2,830)	(3,602)	(5,315)	(1,380)	(1,501)	(4,986)	(0.0111)	(0.0130)	(0.0481)
1.(High Wheat MSP)*	-6,675	-8,232	-13,104	3,990	3,570	-4,715	0.0528***	0.0482**	0.0782
1.(Good Rain Rb)	(7,943)	(9,413)	(15,426)	(2,643)	(3,099)	(5,349)	(0.0192)	(0.0211)	(0.0547)
Observations	2,598	1,857	741	2,598	1,857	741	2,598	1,857	741
R-squared	0.958	0.957	0.983	0.988	0.988	0.991	0.809	0.808	0.890
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Proportion Mean	-0.0480	-0.0570	-0.104	0.0478	0.0438	-0.0534	0.0903	0.0851	0.124

VARIABLES	(10) Full Wheat Yield	(11) High Wheat Yield	(12) Low Wheat Yield	(13) Full Production of Wheat	(14) High Production of Wheat	(15) Low Production of Wheat
1.(Good Early Rain)	-0.0259	-0.00824	-0.0571	9,536*	8,976	36,322
	(0.0363)	(0.0412)	(0.145)	(5,304)	(5,627)	(31,003)
1.(High Wheat MSP)*	0.187***	0.150**	0.364	10,703	11,454	-52,249
1.(Good Rain Rb)	(0.0552)	(0.0622)	(0.250)	(10,695)	(12,144)	(43,061)
Observations	2,598	1,857	741	2,598	1,857	741
R-squared	0.907	0.916	0.928	0.982	0.985	0.985
Early Rainfall in Prediction	Yes	Yes	Yes	Yes	Yes	Yes
MSP in Prediction	No	No	No	No	No	No
Year FE	Yes	Yes	Yes	Yes	Yes	Yes
District FE	Yes	Yes	Yes	Yes	Yes	Yes
State x Time Trends	Yes	Yes	Yes	Yes	Yes	Yes
Proportion Mean	0.0883	0.0728	0.160	0.0412	0.0463	-0.181

*** p<0.01, ** p<0.05, * p<0.1

Standard errors clustered at the district level. 'Low' refers to districts in the bottom 30% of the price distribution in each given year. 'High' refers to the remaining 70% of districts. This analysis excludes all districts that have zero rice production in the kharif season or zero wheat production in the Rabi season for all the years in the sample,and all districts in the states of Rajasthan and Madhya Pradesh. Yield and production specifications also include cubic specifications of monthly rainfall in the post-planting period.

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Table A2.3: Leave-one-out Jackknife Estimates by State (Rice), *Kharif* season Back to text

	Total Area Cultivated	Rice Area	Rice Proportion of Area Cultivated	Rice Yield	Production of Rice
1	-2,715.026	3,342.424	0.040	0.116	14,918.688
	(3,440.737)	(1,493.106)**	(0.013)***	(0.053)**	(9,625.661)
2	-2,373.973	3,716.996	0.043	0.111	14,680.202
	(3,511.123)	(1,528.422)**	(0.014)***	(0.054)**	(9,447.069)
3	-2,715.026	3,342.424	0.040	0.116	14,918.688
	(3,440.737)	(1,493.106)**	(0.013)***	(0.053)**	(9,625.661)
4	-2,640.916	3,604.428	0.042	0.143	17,357.793
	(3,564.549)	(1,562.396)**	(0.014)***	(0.054)***	(9,823.698)*
5	-4,420.329	2,667.692	0.043	0.090	11,893.432
	(3,608.341)	(1,546.972)*	(0.014)***	(0.055)	(9,986.738)
6	-2,667.590	3,356.243	0.039	0.116	15,013.360
	(3,441.381)	(1,494.136)**	(0.013)***	(0.053)**	(9,627.970)
7	-2,765.168	3,286.993	0.040	0.116	12,839.045
	(3,483.211)	(1,515.628)**	(0.014)***	(0.054)**	(9,386.131)
8	-2,715.026	3,342.424	0.040	0.116	14,918.688
	(3,440.737)	(1,493.106)**	(0.013)***	(0.053)**	(9,625.661)
9	-2,715.026	3,342.424	0.040	0.116	14,918.688
	(3,440.271)	(1,492.904)**	(0.013)***	(0.053)**	(9,624.358)
10	-4,312.272	3,441.975	0.040	0.118	15,550.353
	(3,251.550)	(1,536.286)**	(0.014)***	(0.056)**	(10,049.762)
11	-3,158.647	2,997.463	0.039	0.130	15,932.322
	(3,527.852)	(1,498.406)**	(0.014)***	(0.055)**	(9,982.898)
12	-2,866.078	3,533.896	0.054	0.080	15,479.447
	(3,466.593)	(1,510.242)**	(0.013)***	(0.051)	(9,681.397)
13	-2,715.026	3,342.424	0.040	0.116	14,918.688
	(3,440.271)	(1,492.904)**	(0.013)***	(0.053)**	(9,624.358)
14	-4,406.079	2,023.837	0.014	0.142	17,584.005
	(3,495.002)	(1,405.444)	(0.012)	(0.055)***	(9,921.524)*
15	-3,771.047	3,246.985	0.043	0.124	14,690.060
	(3,543.703)	(1,548.162)**	(0.014)***	(0.055)**	(9,806.999)
16	-2,879.326	3,448.405	0.040	0.120	15,397.875
	(3,608.652)	(1,553.257)**	(0.014)***	(0.055)**	(10,009.681)
17	1,533.918	3,833.846	0.039	0.114	15,907.008
	(3,401.072)	(1,565.910)**	(0.014)***	(0.055)**	(10,242.516)
18	-2,283.067	3,570.960	0.043	0.115	15,190.658
	(3,476.787)	(1,553.892)**	(0.014)***	(0.055)**	(9,809.386)
19	-2,777.167	3,341.011	0.040	0.116	14,948.021
	(3,448.734)	(1,497.017)**	(0.013)***	(0.054)**	(9,661.002)
20	-2,726.673	3,346.391	0.040	0.116	14,940.083
	(3,442.149)	(1,493.469)**	(0.013)***	(0.053)**	(9,624.491)
21	-2,715.026	3,342.424	0.040	0.116	14,918.688
	(3,440.737)	(1,493.106)**	(0.013)***	(0.053)**	(9,625.661)
22	-2,661.762	3,360.753	0.040	0.115	14,902.172
	(3,441.604)	(1,494.867)**	(0.013)***	(0.053)**	(9,628.713)
23	-2,068.204	4,344.941	0.042	0.048	9,949.660
	(3,552.382)	(1,513.693)***	(0.014)***	(0.051)	(9,688.847)
24	-2,734.469	3,363.746	0.040	0.116	14,973.620
	(3,445.911)	(1,495.201)**	(0.013)***	(0.053)**	(9,632.170)
25	-1,634.329	3,358.680	0.036	0.125	17,087.773
	(3,514.405)	(1,520.263)**	(0.014)***	(0.056)**	(9,986.824)*
26	-3,266.106	3,271.340	0.039	0.122	14,764.370
	(3,492.685)	(1,511.951)**	(0.014)***	(0.054)**	(9,862.856)
27	-2,715.026	3,342.424	0.040	0.116	14,918.688
	(3,440.737)	(1,493.106)**	(0.013)***	(0.053)**	(9,625.661)
28	-1,009.402	3,314.318	0.029	0.081	7,752.261
	(3,655.043)	(1,737.931)*	(0.011)***	(0.045)*	(7222.477)
29	-3,351.619	3,411.073	0.043	0.137	16,713.695
	(3,560.298)	(1,556.973)**	(0.014)***	(0.055)**	(10,060.946)*
30	-2,607.378	3,458.748	0.040	0.120	15,510.199
	(3,473.227)	(1,511.843)**	(0.014)***	(0.054)**	(9,749.161)
31	-203.589	5,223.755	0.046	0.214	32,410.098
	(3,947.901)	(1,721.362)***	(0.016)***	(0.073)***	(13,407.322)**
32	-2,887.329	3,309.690	0.040	0.118	14,844.629
	(3,506.642)	(1,510.259)**	(0.014)***	(0.055)**	(9,829.899)

Table A2.4: Leave-one-out Jackknife Estimates by State (Wheat), *Rabi* season Back to text

State Excluded	Total Area Cultivated	Wheat Area	Wheat Proportion of Area Cultivated	Wheat Yield	Production of Wheat
1	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,361.473)	(2,133.515)	(0.014)*	(0.048)***	(8,053.790)***
2	-10,159.133	352.431	0.023	0.190	21,095.094
	(7,360.220)	(2,132.011)	(0.014)*	(0.048)***	(8,048.350)***
3	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,357.308)	(2,132.308)	(0.014)*	(0.048)***	(8,049.235)***
4	-10,299.551	495.664	0.024	0.190	22,028.000
	(7,587.063)	(2,226.691)	(0.014)*	(0.049)***	(8,400.560)***
5	-12,276.823	-455.290	0.023	0.151	18,118.098
	(7,626.272)	(2,122.878)	(0.014)	(0.048)***	(8,193.088)**
6	-10,155.486	335.601	0.023	0.194	21,047.500
	(7,361.068)	(2,132.142)	(0.014)*	(0.048)***	(8,048.120)***
7	-9,727.381	664.879	0.026	0.197	22,097.885
	(7,486.715)	(2,154.998)	(0.014)*	(0.048)***	(8,184.793)***
8	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,361.473)	(2,133.515)	(0.014)*	(0.048)***	(8,053.790)***
9	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,361.473)	(2,133.515)	(0.014)*	(0.048)***	(8,053.790)***
10	-15,376.751	-1,112.667	0.014	0.106	12,845.268
	(8,350.440)*	(1,441.902)	(0.014)	(0.045)**	(5,558.498)**
11	-10,762.203	54.596	0.020	0.194	21,334.894
	(7,565.564)	(2,147.067)	(0.014)	(0.049)***	(7,957.791)***
12	-9,713.937	541.996	0.030	0.170	20,452.874
	(7,502.831)	(2,154.290)	(0.013)**	(0.048)***	(8,179.771)**
13	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,361.473)	(2,133.515)	(0.014)*	(0.048)***	(8,053.790)***
14	-10,631.872	190.622	0.020	0.202	22,307.833
	(7,587.330)	(2,191.757)	(0.012)	(0.048)***	(8,269.579)***
15	-9,875.742	511.950	0.025	0.190	21,860.378
	(7,545.507)	(2,215.730)	(0.014)*	(0.049)***	(8,397.622)***
16	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,361.473)	(2,133.515)	(0.014)*	(0.048)***	(8,053.790)***
18	2,639.960	937.144	0.020	0.220	23,376.513
	(4,099.020)	(2,513.737)	(0.016)	(0.052)***	(9,883.903)**
19	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,361.473)	(2,133.515)	(0.014)*	(0.048)***	(8,053.790)***
20	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,361.473)	(2,133.515)	(0.014)*	(0.048)***	(8,053.790)***
21	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,361.473)	(2,133.515)	(0.014)*	(0.048)***	(8,053.790)***
22	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,358.682)	(2,132.706)	(0.014)*	(0.048)***	(8,050.737)***
23	-10,986.271	317.249	0.012	0.226	21,804.949
	(7,654.842)	(2,183.843)	(0.013)	(0.047)***	(8,307.409)***
24	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,361.473)	(2,133.515)	(0.014)*	(0.048)***	(8,053.790)***
25	-10,657.993	-279.150	0.019	0.183	16,996.442
	(7,456.585)	(2,113.214)	(0.014)	(0.049)***	(7,804.578)**
27	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,361.473)	(2,133.515)	(0.014)*	(0.048)***	(8,053.790)***
28	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,360.100)	(2,133.117)	(0.014)*	(0.048)***	(8,052.288)***
29	-10,198.387	354.944	0.023	0.192	21,158.492
	(7,363.932)	(2,133.174)	(0.014)*	(0.048)***	(8,059.735)***
30	-10,162.863	354.489	0.023	0.191	21,109.362
	(7,361.473)	(2,133.515)	(0.014)*	(0.048)***	(8,053.790)***
31	-14,331.462	1,926.886	0.049	0.230	22,482.760
	(9,809.050)	(2,760.303)	(0.019)***	(0.063)***	(9,927.051)**
32	-11,165.413	439.902	0.025	0.202	23,651.840
	(7,933.434)	(2,335.142)	(0.015)*	(0.050)***	(8,683.103)***

A3 Model Appendix

A3.1 CES Equilibrium

A3.1.1 Without Price Supports

According to the framework, we have the following equations from the FOCs:

$$q_M = \frac{(1-\alpha)^\sigma I}{\alpha^\sigma p_A^{1-\sigma} + (1-\alpha)^\sigma} \tag{A3.1}$$

$$\beta_i p_i z_i (\frac{K_i}{L_i})^{\beta_i - 1} = r \tag{A3.2}$$

$$(1-\beta_i) p_i z_i (\frac{K_i}{L_i})^{\beta_i} = w \tag{A3.3}$$

$$p_A = \frac{\beta_M z_M}{\beta_A z_A} (\frac{K_M}{L_M})^{\beta_M - 1} (\frac{K - K_M}{L - L_M})^{1-\beta_A} \tag{A3.4}$$

$$y_M = q_M = \frac{E_M}{p_M} = E_M \tag{A3.5}$$

$$K = K_M + K_A \tag{A3.6}$$

$$L = L_M + L_A \tag{A3.7}$$

$$I = wL + rK \tag{A3.8}$$

First, I rewrite K_M in terms of L_M using A3.2, A3.3, A3.6, and A3.7:

$$K_M = \frac{(1-\beta_A)\beta_M}{(1-\beta_M)\beta_A} \frac{K - K_M}{L - L_M} L_M \tag{A3.9}$$

$$= \frac{(1-\beta_A)\beta_M K L_M}{(1-\beta_M)\beta_A L + (\beta_M - \beta_A) L_M} \tag{A3.10}$$

Then, I use the market clearing condition from equation A3.5, together with A3.1, and A3.8 to express L_M in terms of p_A.

$$y_M = q_M \tag{A3.11}$$

$$z_M K_M^{\beta_M} L_M^{1-\beta_M} = \frac{(1-\alpha)^\sigma}{\alpha^\sigma p_A^{1-\sigma} + (1-\alpha)^\sigma}(wL + rK) \tag{A3.12}$$

I substitute in for w and r using A3.2 and A3.3:

$$z_M K_M^{\beta_M} L_M^{1-\beta_M} = [\frac{(1-\alpha)^\sigma}{\alpha^\sigma p_A^{1-\sigma} + (1-\alpha)^\sigma}]((1-\beta_M) z_M (\frac{K_M}{L_M})^{\beta_M} L + \beta_M z_M (\frac{K_M}{L_M})^{\beta_M - 1} K) \tag{A3.13}$$

I divide through by $z_M(\frac{K_M}{L_M})^{\beta_M}$, then substitute in for K_M using A3.10, and rearrange, to get a implicit expression for L_M:

$$L_M[(\frac{\alpha}{1-\alpha})^\sigma p_A^{1-\sigma} + \frac{1-\beta_M}{1-\beta_A}] - \frac{1-\beta_M}{1-\beta_A} L = 0 \tag{A3.14}$$

Finally, I use equation A3.4 and substitute in for K_M using A3.10, to obtain an expression for p_A in terms of L_M and constants:

$$p_A = \frac{\beta_M z_M}{\beta_A z_A}(\frac{K_M}{L_M})^{\beta_M - 1}(\frac{K - K_M}{L - L_M})^{1-\beta_A} \tag{A3.15}$$

$$= \frac{\frac{\beta_M[\beta_A(1-\beta_M)]^{1-\beta_A}}{\beta A[\beta_M(1-\beta_A)]^{1-\beta_M}} z_M}{z_A}[\frac{K}{(1-\beta_M)\beta_A L + (\beta_M - \beta_A)L_M}]^{\beta_M - \beta_A} \tag{A3.16}$$

A3.1.2 With Price Supports

When price supports are set at the level p_S in the agricultural sector, with a consumer price for agricultural goods set at p_C, I start with a modified set of first-order conditions. I rewrite A3.4 as follows:

$$p_S = \frac{\beta_M z_M}{\beta_A z_A}(\frac{K_M}{L_M})^{\beta_M - 1}(\frac{K - K_M}{L - L_M})^{1-\beta_A} \tag{A3.17}$$

Then, I substitute for K_M using A3.10, and rearrange to get:

$$p_S = \frac{\beta_M z_M}{\beta_A z_A} \frac{[(1-\beta_A)\beta_M]^{\beta_M - 1} K^{\beta_M - \beta_A}[(1-\beta_M)\beta_A]^{1-\beta_A}}{[(1-\beta_M)\beta_A L + (\beta_M - \beta_A)L_M]^{\beta_M - \beta_A}} \tag{A3.18}$$

Rewriting in terms of L_M,

$$L_M = \frac{(\frac{[(1-\beta_A)\beta_M]^{\beta_M - 1}[(1-\beta_M)\beta_A]^{1-\beta_A} K^{\beta_M - \beta_A}}{p_S z_A})^{\frac{1}{\beta_M - \beta_A}} - (1-\beta_M)\beta_A L}{\beta_M - \beta_A} \tag{A3.19}$$

A3.2 CES Comparative Statics

Now, I derive various relevant comparative statics for the two different cases.

A3.2.1 Without Price Supports

Labor in Manufacturing
I substitute A3.16 into A3.14 to get:

$$L_M[\kappa_1(\frac{\kappa_3 z_M}{z_A})^{1-\sigma}(\frac{K}{(1-\beta_M)\beta_A L + (\beta_M - \beta_A)L_M})^{(\beta_M - \beta_A)(1-\sigma)} + \kappa_2] - \kappa_2 L = 0 \tag{A3.20}$$

$$\tag{A3.21}$$

As long as $\sigma < 1$, an increase in z_A decreases the left-hand side of the equation. The effective size of the exponent on L_M is positive, so it is clear that L_M must increase in response to an increase in z_A to keep the system in equilibrium.

$$\frac{\partial L_M}{\partial z_A} > 0$$

Relative Price of Agricultural Goods
From A3.16, and since $\frac{\partial L_M}{\partial z_A} > 0$, an increase in z_A results in a decrease in p_A.

$$\frac{\partial p_A}{\partial z_A} < 0$$

Production in Manufacturing
From A3.1, it is clear that q_M increases as p_A falls, which happens in response to an increase in z_A. Therefore,

$$\frac{\partial q_M}{\partial z_A} > 0$$

Labor in Agriculture
With a given total stock of labor, L,

$$\frac{\partial L_A}{\partial z_A} = -\frac{\partial L_M}{\partial z_A} < 0$$

Production in Agriculture
Agricultural production is influenced by two different pressures: 1. The posiive effect of increased agricultural productivity z_A, and 2. The resulting decrease in capital and labor allocated to agriculture in equilibrium.

Overall, using equations A3.1 and the budget constraint from the household problem, we have:

$$q_A = \frac{I\alpha^\sigma}{p_A^\sigma(\alpha^\sigma p_A^{(1-\sigma)} + (1-\alpha)^\sigma)} \tag{A3.22}$$

Since we know agricultural prices fall with a positive productivity shock,

$$\frac{\partial q_A}{\partial z_A} > 0$$

However, I should note that the amount of rice produced in response to a positive productivity shock actually *falls* in my empirical analysis, due to substitution with other crops, which the model cannot capture.

A3.2.2 With Price Supports

I now turn to the version of the model with price supports. The equilibrium is defined in equation 18:

$$L_M = \frac{(\frac{\kappa_4}{p_S z_A})^{\frac{1}{\beta_M-\beta_A}} - \kappa_5}{\beta_M - \beta_A}$$

Labor in Manufacturing

$$\frac{\partial L_M}{\partial z_A} = \frac{-1}{(\beta_M-\beta_A)^2}(\frac{\kappa_4}{p_S})^{\frac{1}{\beta_M-\beta_A}}(\frac{1}{z_A})^{\frac{1-\beta_M+\beta_A}{\beta_M-\beta_A}}\frac{1}{z_A^2} < 0 \tag{A3.23}$$

Production in Manufacturing
From A3.10, K_M decreases when L_M falls, which happens in response to an increase in z_A. Therefore, overall manufacturing production, q_M, falls.

$$\frac{\partial q_M}{\partial z_A} < 0 \tag{A3.24}$$

Labor in Agriculture
With a given total stock of labor, L

$$\frac{\partial L_A}{\partial z_A} = -\frac{\partial L_M}{\partial z_A} > 0$$

Production in Agriculture

With a given stock of capital and labor, and equations A3.23 and A3.10, we know that K_A and L_A both increase in response to a positive productivity shock z_A. Therefore,

$$\frac{\partial q_A}{\partial z_A} > 0 \tag{A3.25}$$

Size of the effect relative to the level of the price support

The effect of the level of the price support on the size of the labor and production effects can be determined from equation A3.19.

$$\frac{\partial L_M}{\partial z_A \partial p_S} = \kappa_4^{\frac{1}{\beta_M - \beta_A}} \frac{1}{(\beta_M - \beta_A)^3} \left(\frac{1}{p_S z_A}\right)^{\frac{1-\beta_M+\beta_A}{\beta_M-\beta_A}} \frac{1}{z_A^2} \frac{1}{p_S^2} > 0 \tag{A3.26}$$

This suggests that the negative effect of the productivity shock on labor allocated to manufacturing is larger when price supports are higher.

A4 Data Appendix

A4.1 Crops by Category

Category	Crops
Other Cereals	Bajra, Barley, Jowar, Maize, Ragi, Wheat, Small Millets, Others
Pulses	Arhar/Tur, Beans, Blackgram, Cowpeas, Gram, Horsegram, Khesari, Masoor, Moth, Greengram, Urad, Other pulses
Cash Crops and Oilseeds	Arecanut, Cashewnut, Castorseed, Cotton, Coconut, Groundnut, Guarseed, Hemp, Jute, Linseed, Mesta, Nigerseed, Safflower, Sesamum, Sugarcane, Soybeans, Sunflower, Tobacco
Spices	Black pepper, Cardamom, Coriander, Dry Chillies, Dry Ginger, Garlic, Ginger, Turmeric

A4.2 Crops Used in the Productivity Calculation

Jowar, bajra, maize, barley, small millets, ragi, gram, arhar/tur, moong, masoor, urad, peas, groundnut, cotton.

Data Type	Data Source	Notes
Output		
District-level Production of Various Crops	APY data	
District-level crop prices	District-level averages of prices faced by households in that district for each crop in the NSS consumption/expenditure data	Rounds 60-68, Schedule 1.0. Soybean is not reported in NSS rounds 66 and 68. Cotton is not reported in NSS round 68. Revenue shares are adjusted accordingly. Where a crop's prices are not available for a particular district, I replace the missing data with the state-average price for the crop.
Inputs		
Land use in agriculture	APY data	
Quantities and price of labor	NSS Employment/Unemployment Surveys	Rounds 60-68, Schedule 10. To obtain correct labor cost share estimates, I aggregate up the NSS data using the multipliers provided.

Data Type	Data Source	Notes
Fertilizer Use (N, P, and K)	Agricultural Input Survey 2006-07	The survey does not provide season-wise input use, so, to the extent that the cost shares of other inputs are high relative to labor, the effect of the labor-use increase in high MSP years is understated, resulting in a lower-bound estimate of the fall in agricultural productivity.
Use of agricultural machinery	Agricultural Input Survey 2006-07	
Use of irrigation	Agricultural Input Survey 2006-07	
Use of high-yielding varieties	Agricultural Input Survey 2006-07	
Prices of non-labor inputs	Cost of Cultivation Survey 2006-07	Prices are aggregated to the state-level.

A4.3 Absolute and Relative Suitability

Absolute suitability for rice and wheat is simply the value of the Suitability Index for the district. Relative suitability is arguably a more important measure, since a district that is absolutely bad for staple production could still do relatively better by planting staples than by planting other crops (that have absolutely worse letterpaper suitability measures). It also captures the district's comparative (rather than absolute) advantage, a key determinant of potential gains from trade.

To calculate the relative suitability of crops, I weight the absolute suitability levels by the average share of the country's land area used in the production of that crop in the main growing season (to avoid placing too high a weight on the suitability of a district to grow more minor crops). I then calculate an overall index of suitability for the district:

$$CropIndex_{ds} = \sum_{j=1}^{16} AreaProp_j \, Suit_{js}$$

I then calculate the relative suitability of the staple crops by taking:

$$RelSuitRice_{ds} = \frac{SuitRice_{ds} - CropIndex_{ds}}{CropIndex_{ds}}$$

with an analogous measure for relative wheat suitability. I then run analyses separately for low- and high-suitability districts (dividing the sample by the median of the relative suitability measure).