The effect of warehouse receipt finance on farmers' terms of trade: Evidence from India*

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We study the effect of warehouse receipt financing on terms of trade for farmers. With limited access to credit and storage facilities, farmers are compelled to sell their produce immediately after harvest at unfavourable prices. Warehouse receipt systems allow farmers to obtain loans with the crop kept in the warehouse as collateral. Using detailed price data from rural crop markets across India, we assess the effectiveness of a reform passed in 2007 to establish a warehouse receipt system, in improving crop prices for farmers and reducing seasonal price volatility. We compare outcomes in markets in close vicinity to a new program warehouse in the period after the warehouse registered to the program, to the period before and to markets further away from a program warehouse in both periods. We find a positive and persistent effect of warehouse receipt financing on prices received by farmers, and a reduction in inter-seasonal price volatility as a result of the treatment.

Keywords: Post-harvest credit, Diff-in-diff, Agricultural markets, Price seasonality, Storage

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1 Introduction

Warehouse receipt finance has received substantial interest as an instrument to improve trading conditions and market access for small scale farmers in developing countries (Onumah (2013), Coulter and Onumah (2002), Hollinger et al. (2009), Lacroix and Varangis (1996)). Although present in African countries since the liberalization wave in the 1980's, it has mostly catered to imported goods and large exporting operations. Multiple warehouse receipt pilots and initiatives have been launched by NGO's in different countries in sub-Saharan Africa, aiming to improve access for small scale farmers. However, as noted by Coulter (2009) in a review undertaken on behalf of UNCTAD, "progress in developing WRS in Africa, has been frustratingly slow".

Insufficient access to institutional credit and to adequate storage facilities hampers the ability of small scale farmers to transfer wealth across time (Le Cotty et al. (2019)). To meet household consumption needs and repay production loans, farmers are often obligated to sell their produce at an unfavorable price right after harvest. Moreover, a phenomenon of "selling low and buying high" has been recorded among poor farmers who effectively buy their produce back at higher prices from the market, as the household stocks dwindle before the next harvest (Barret (2006) for rice in Madagascar; Stephens and Barret (2011) for Maize in western Kenya; Burke et al. (2019) also for Maize in Kenya). The pattern of selling crops close to harvest also produces patterns of sharp seasonal price fluctuations, which are a common characteristic of staple crops in many developing countries (Sahn, 1989). The resulting opportunities for inter-temporal arbitrage are then mostly exploited by large producing enterprises, while small farmers are found to experience a decline in welfare due to the increase in price variability (Barret and Dorosh (1996)). Food consumption as well as total consumption in rural households were found to decrease during the lean season pointing to a decline in welfare (Kaminski et al. (2014), Basu and Wong (2015)).

Warehouse receipt systems are expected to provide growers of storable crops with liquidity (coupled with adequate storage conditions) allowing them to wait for higher prices rather than selling their produce at unfavorable terms right after harvest. By such means they are also expected to reduce crop price fluctuations across time. If warehouse receipt financing were indeed made available to small farmers who effectively borrow on account of their crops using the "sell low and buy high" practice, it will likely prove less costly than engaging in such inter-temporal arbitrage to gain liquidity (for example, in Madagascar the mean quarterly change in prices was 29% while the mean annual interest rate was only 27%).

Several studies have attempted to evaluate the effects of credit or storage interventions (or combinations of the two) on outcome for farmers using a local experimental approach.

Burke et al. (2019) conducted a field study among Maize farmers in Kenya, randomly offering farmers a loan at harvest, and studied the treatment effect on sales and purchasing patterns by farmers and on market prices. They found that farmers sold less and bought more maize after harvest. The authors also found an inter-temporal convergence of prices in nearby markets following the intervention. In Fink et al (2014), The researchers offered small-scale farmers from randomly selected villages in rural Zambia a loan of up to 75 kgs of ground maize, an amount consumed in three by an average household rural Zambia. In the paper, they develop a theoretical model of a market for out-of-farm labor, and find that in-line with the model's predictions, offering loans reduces the labor supply of out-of-farm work, increased wages and food security.

Basu and Wong (2015) also used an experimental approach by randomly offering one of two interventions: a seasonal storage program or credit in the form of crops, to staple farmers in west Timor, Indonesia. They found no effect on staple food consumption, the storage program increased non-food consumption and the credit program increased reported income and reduced seasonal gaps in consumption. Negede et al. (2024) offered hermetic storage bags to maize farmers in Ethiopia in a randomized trial. They found an extended storage period due to the treatment but no effect on welfare indicators.

Similarly, In Channa et al (2022), the researchers conduct a random controlled trial. In the experiment, they compare outcomes of villages that were offered a loan against a maize stock stored in hermetic bags, to those offered only hermetic storage bags, to those of a control group. They found that by itself the storage intervention did not have a significant effect on the amount of maize stored or sold, but when combined with the credit intervention, there is a substantial effect on sales and storage. A closely related concept to WRS is warrantage.

In warrantage systems, rural banks offer credit against harvest stored for a period of six months as collateral. The key difference between warrantage and WRS is that in the later, farmers can withdraw their stored harvest at anytime. In Le Cotty et al. (2019), the researchers find a link between hyperbolic time preferences and participation in warrantage, pointing that another way storage-solutions can benefit farmers is by being a device for self-control.

Our analysis on the recent warehouse receipt reform in India aims to complement this emerging literature. We are not aware of another comprehensive study of the market effects of a new warehouse receipt financing program. The rich market data available coupled with locations and timing of warehouses joining the WDRA system, provide an opportunity to study the effect of a program linking credit to storage on market interactions and farmer behavior. We use detailed price data from around 2,000 rural markets across India, including prices and market arrivals of storable and non-storable. To evaluate the effect of a WDRA warehouse on market outcomes, we compare prices and arrivals in markets "near" a new warehouse in the time after the warehouse joined the program to the time period before, and to outcomes in markets further away from a new warehouse. We find a positive and persistent effect on prices for farmers selling storable crops in the treated markets. We also find a reduction in inter-seasonal price volatility (particularly during the main harvest season). The rest of the paper is organized as follows, Chapter 2 describes the market and warehouse data used for the analysis, Chapter 3 presents the methodology and main specifications; Chapter 4 presents the difference-in-differences and event study results and Chapter 5 concludes.

2 Data

2.1 Price data

For information on market outcomes, we collected prices and arrivals in around 2,000 Indian mandis[1] for the years between 2011 and 2018. The daily data was aggregated to a monthly frequency (aggregated prices were weighted by quantities). Crops were chosen in a way to represent both storable crops (covered by the WDRA) and non-storable crops sold in the same markets[2].

2.2 WDRA Warehouses

Characteristics of the WDRA warehouses were obtained from the Warehousing Development and Regulatory Authority (Dept. of food and public distribution, GOI). The data includes name and address of the warehouse, the warehousing company it belongs to, phone number, capacity, date of registration with WDRA (and the date up to which the registration is valid). About 44% of the warehouses are provided by public warehousing enterprises, the largest of which are the Central Warehousing Corporation (with 129 warehouses), National Bulk Handling Corporation (with 91) and National Collateral Management Services (with 84). The rest are private enterprises. About 37% of the private enterprises are companies with at least 3 warehouses, the largest of which are Star-Agri with 74 warehouses, LTC (with 62) and Kalyx (with 42). The remaining 19% of the private enterprises are small businesses, usually registered to an individual and with only one warehouse in most cases. Table 1

[1]Mandis are regulated rural markets where farmers sell their produce to licensed traders.

[2]The list of storable crops used: Cotton, Groundnut, Jowar, Maize, Masur Dal, Paddy, Red Grams, Rice, Wheat. The list of non-storable crops: Onion, Potato, Tomato, Banana, Ginger, Pumpkin, Orange, Papaya, Apple, Pomegranate.

presents the evolution of program warehouses in the different Indian states between 2011 and 2018. Since most warehouses joined between 2016 and 2018 we focus our analysis on these years and the three years before, starting at 2013.

Table 1: WDRA warehouses, by state year

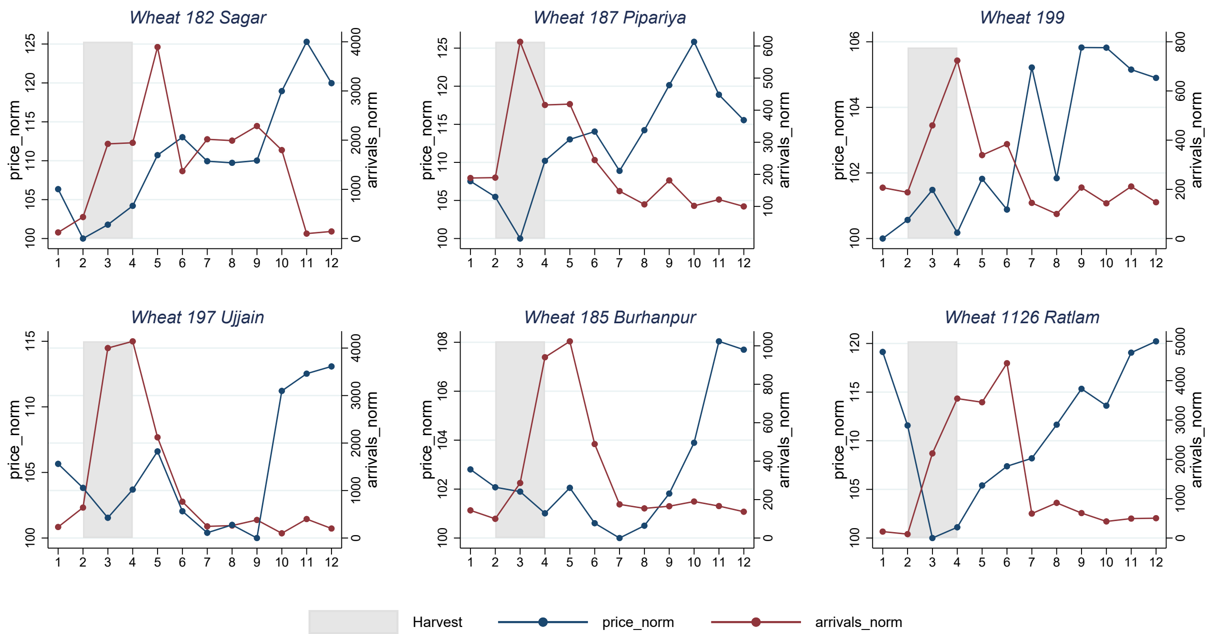
State	2011	2012	2013	2014	2015	2016	2017	2018
Andhra Pradesh						3		24
Assam							1	1
Bihar						1	1	6
Gujarat			2			11	66	54
Haryana							2	6
Jharkhand								1
Karnataka						15	1	20
Kerala		1				1	5	2
Madhya Pradesh	1	3	10	1	1	34	59	69
Maharashtra						9	30	39
Odisha								2
Puducherry							1	
Punjab								5
Rajasthan	6			9		15	52	83
Tamil Nadu						1	19	2
Telangana							2	19
Tripura								1
Uttar Pradesh	2						2	29
West Bengal								1

Source: The Warehousing Development and Regulatory Authority (Dept. of food and public distribution, GOI).

2.3 Seasonality

A descriptive analysis of the price and arrivals data, shows strong seasonal patterns, even for storable crops. Figures 1 shows these patterns for 6 large markets trading in wheat in the state of Madhya Pradesh for the time period before 2016. The wheat harvesting season is marked in grey in each sub-graph. A substantial low in prices is evident across the markets around the harvest season. Arrivals present a mirror image or substantial spikes in quantities arriving at these markets during this time. Although theoretically farmers should be able to store wheat awaiting favourable terms of trade, it appears that such opportunities are not taken advantage of to an extent that would mitigate the seasonal patterns.

Figure 1: Wheat seasonality - large MP wheat markets



Notes: The data for prices and arrivals here is from the years 2011-2015 averaged by calendar months for six largest wheat markets in the state of Madhya Pradesh. We normalized both average prices and market arrivals such that the lowest value is indexed as 100. The price is plotted in blue against the left-hand y-axis, and arrivals are plotted in red against the right-hand y-axis. The main wheat harvest season is shaded in grey. Strong seasonal patterns are evident for both prices and arrivals. Prices generally hit a low around the harvest season, and reach a high (115%-125%) around October-November. Arrivals present a mirror image.

3 Methodology

3.1 Difference-in-differences

To analyse the effect of a WDRA warehouse on market outcomes we first employ a difference-in-difference specification with fixed effects, where the treatment group are markets "near" a new warehouse, and the treatment period is the time since the warehouse registration. Control markets are those "far away" from a WDRA warehouse. The baseline specification is:

$$y_{cmt} = \alpha + \beta(Treatment_m \times After_{mt}) + \delta_c + \delta_m + \delta_t + \epsilon_{cmt} \tag{1}$$

where y_{cmt} is an outcome of interest (ln(prices) or ln(arrivals)) for crop c in market m at month t. δ_c, δ_m, and δ_t are crop, market and month-year fixed effects, respectively. ϵ_{cmt} are error terms clustered at the district level to adjust for possible geographical and inter-temporal correlation between market outcomes for markets in the same district. $Treatment_m$ is a dummy variable assigned the value of 1 for markets *near* a WDRA warehouse, and 0 for markets *far away* from a WDRA warehouse. $After_{mt}$ is a dummy variable receiving the value 1 for the period after a WDRA warehouse near market m has joined the program, and 0 in the time periods before.

Two points on specification are in place here, one on treatment aggregation and the other on treatment cutoff. First, it is not straight forward to define which markets are close enough to a warehouse to be defined as treated by it. To gain some perspective we considered the average distanced between markets and warehouses and between neighboring markets and neighboring warehouses (summarized in Table 2 for the year 2018 (the one with the most warehouses in our data)).

Table 2: Minimum distances, summary statistics

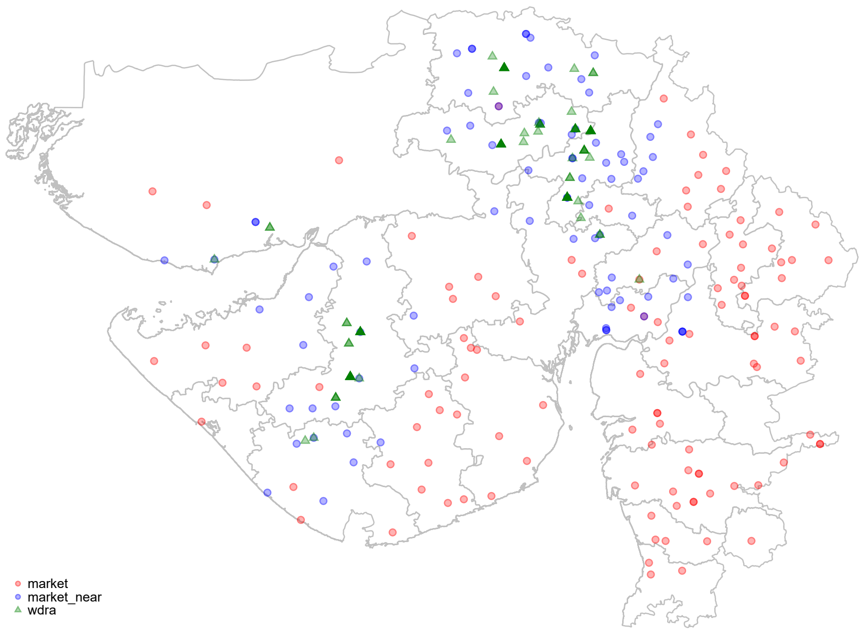
Variable	Obs.	Mean	Std. Dev.	Min	Max
Distance from each market to nearest warehouse, all states 2018	2,439	63.4	57.8	0	296
Distance from each warehouse to nearest market, 2018	698	9.6	8.4	0	40.8
Distance from each WDRA to nearest other WDRA, 2018	698	29.5	32.3	1.6	345.7
Distance from each Market to nearest other Market	2,439	19.2	11.4	0.2	126.2

Considering the distribution of distances from each WDRA warehouse to the nearest rural market, we can think of 40km as a lower boundery on the furthest treated market (if we indeed think of markets as the treated units) since if some WDRA warehouse if as far as 40km from the nearest market and should potentially treat at least one market (or the farmer population around it), then this market should be included in the treatment group. Another statistic of interest is the average distance between a market and the nearest WDRA warehouse to it, which is around 63km. This distribution includes also much larger distances (up to 296km - markets around this tail are definitely in the "control" group). For the main tables in the result section we present analysis results where the treatment cutoff is defined at 60km (see Figure 2 for a depiction of treatment and control markets in the state of Gujarat).[3]

The second point on specification to notice is, since each market may be treated by multiple WDRA warehouses, some aggregation of treatment needs to be defined. We use three alternative specifications. The first defines each market treated by at least one warehouse as treated, regardless of the number of warehouses within its vicinity. The second counts the number of WDRA warehouses within the cutoff distance to the market, thus creating a weighted treatment index which may differ by market. The third specification aggregates the total capacity of warehouses within the cutoff distance from the market, to generate an

[3]We performed robustness checks for alternative cutoffs at 50km and 70km, which had no substantial effect on the results.

Figure 2: Treatment and control markets, Gujarat



even more precise measure of treatment intensity.

Since non-storable crops cannot be stored and are not covered by the WDRA program, they should not be affected directly by the program, although some indirect effects may create spillovers to this group of crops as well (for example farmers switching between types of crops, or using the change in liquidity from one stored crop for bargaining power in another crop[4]). To evaluate the differential effect for storable and non-storable crops we include an interaction treatment term:

$$y_{cmt} = \alpha + \beta(Treatment_m \times After_{mt}) + \gamma(Treatment_m \times After_{mt} \times Storable_c) + \delta_c + \delta_m + \delta_t + \epsilon_{cmt} \tag{2}$$

where $Storable_c$ receives the value 1 if crop c is storable and 0 otherwise.

3.2 Event studies

In order to evaluate the dynamics of the estimated effect in the difference-in-differences specifications we conduct event studies focusing on the months before and after the first WDRA warehouse is registered in the vicinity of each market. This specification replaces

[4]although since non-storable crops have a smaller window for sale in any case, the additional liquidity may not substantially affect their bargaining power

the treatment variable with a set of month-since-first-WDRA dummy variables:

$$y_{cmt} = \alpha + \sum_{t=-T}^{T} \beta_t + \delta_c + \delta_m + \delta_t + \epsilon_{cmt} \tag{3}$$

we run this specification separately for prices and arrivals and for storable and non-storable crops.

3.3 Seasonality

To evaluate changes in seasonality in prices and market arrivals following the introduction of a WDRA warehouse, we regress the outcome variables on calendar-month dummies. We do this separately for the treatment-after and the control groups for storable crops.

$$y_{cmt} = \alpha + \sum_{i=1}^{12} month_i + \delta_c + \delta_m + \delta_y + \epsilon_{cmt} \tag{4}$$

where $month_i$ are calendar-month dummies and δ_c, δ_m, δ_y are crop, market and year fixed effects.

4 Results

4.1 Difference-in-Differences

Table 3 presents the difference-in-differences results for the effect of WDRA warehouse availability on log prices. We restrict our sample to markets only in states with any WDRA warehouses in any of the years for a closer comparison group and use monthly time periods between 2013-2018.

Table 3: Diff-in-Diff, Mandi prices

VARIABLES	(1) Log-price any	(2) Log-price number	(3) Log-price capacity
$Treatment \times After$	-0.047**	-0.008***	-0.0007***
	(0.018)	(0.002)	(0.0002)
$Treatment \times After \times Storable$	0.115***	0.011***	0.0012***
	(0.028)	(0.002)	(0.0002)
Combined effect storable	0.068	0.003	0.0005
P-val for combined effect	0.000	0.000	0.000
Observations	438,555	438,555	438,555
R-squared	0.6603	0.66	0.6599
Makret FE	Yes	Yes	Yes
Crop FE	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes

Treatment defined at the 60km boundary; Only states ever treated included and the years 2013-2018; Standard errors are clustered at the district level; $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Columns (1)-(3) present the estimated effects for storable and non-storable crops with the treatment variables: any-WDRA, number of WDRAs and total capacity of WDRAs in the vicinity of the market, respectively. For storable crops, we find an average 6.8% increase in mandi prices for being treated any WDRA warehouse, an average 0.3% increase per WDRA warehouse, and a 0.005% increase per 1000 tons increase in WDRA capacity. For non-storable crops, surprisingly, we find negative and statistically significant effects (4.7% decrease for any WDRA, 0.8% decrease per WDRA warehouse, and 0.007% decrease per 1,000 tons in capacity).

Table 4 presents a similar analysis for log-arrivals as the dependant variable. Here, we generally find no statistically significant effect on quantities for either storable or non-storable crops. Only in the specification using the number of warehouses as treatment we find a combined negative effect for storable crops that is marginally statistically significant (p-value of 0.079).[5]

[5] The coefficient on the treatment interacted with storable is actually positive and the combined effect is only negative because it is smaller in size compare to the non-interacted term.

Table 4: Diff-in-Diff, Mandi arrivals

VARIABLES	(1) Log-arrivals any	(2) Log-arrivals number	(3) Log-arrivals capacity
$Treatment \times After$	-0.037	-0.011	-0.0018
	(0.069)	(0.012)	(0.0013)
$Treatment \times After \times Storable$	0.029	0.006	0.0012
	(0.105)	(0.014)	(0.0017)
Combined effect storable	-0.008	-0.006	-0.0006
P-val for combined effect	0.889	0.079	0.267
Observations	439,408	439,408	439,408
R-squared	0.5301	0.5301	0.5301
Makret FE	Yes	Yes	Yes
Crop FE	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes

Treatment defined at the 60km boundary; Only states ever treated included and the years 2013-2018; Standard errors are clustered at the district level; $^{*}**p < 0.01$, $^{*}*p < 0.05$, $^{*}p < 0.1$

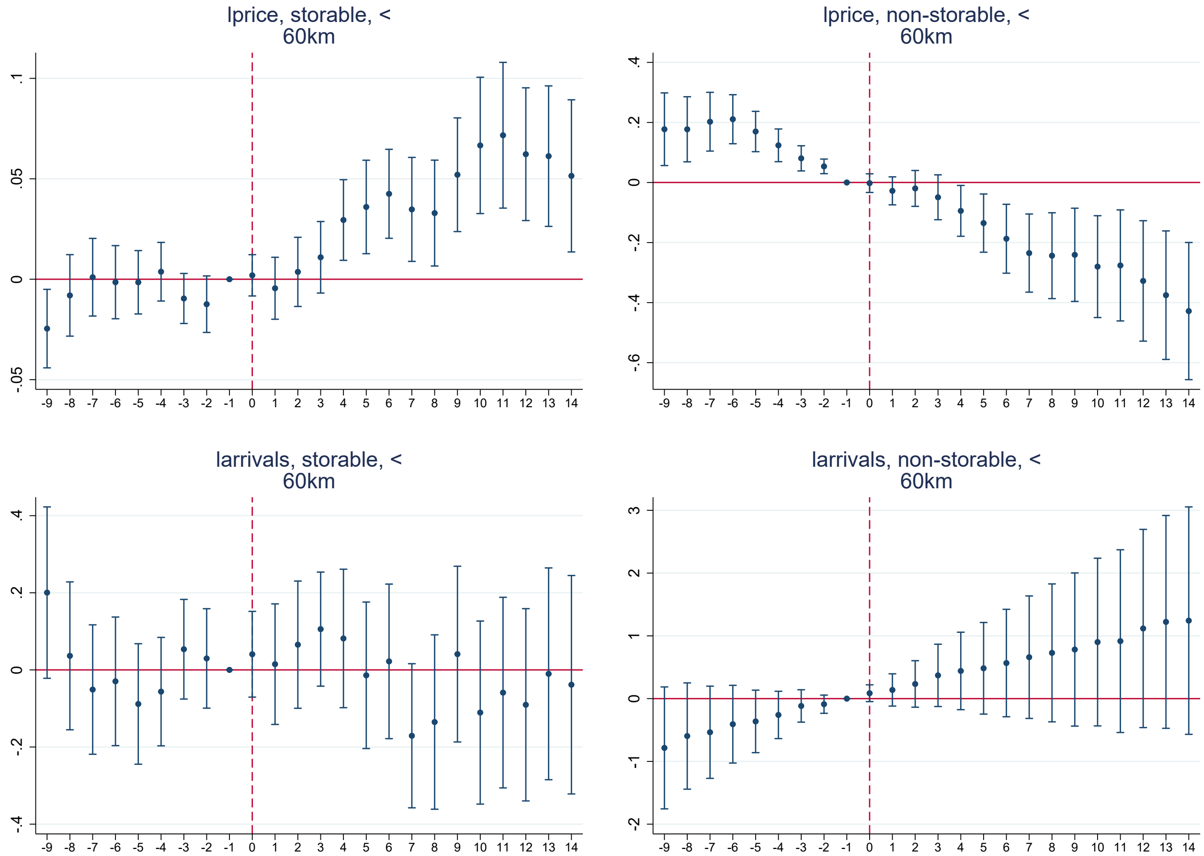
4.2 Event Studies

Figure 3 presents the coefficient plots from the event studies (and Table 5 presents the respective regression results). The top panel presents the results for log-prices, and the bottom panel presents results for log-arrivals. The month before the registration of the first WDRA warehouse is used as the baseline category for the analysis (t=-1). In the case of storable crops, most coefficients are not statistically significant in the periods before the first WDRA warehouse, supporting the no pre-trend assumption for the diff-in-diff.[6] From the 4th month after the first warehouse we find a positive and statistically significan effect on prices, which remains and even increases in magnitude up until 14 months after period 0.

For arrivals in the case of storable crops, there is neither a statistically significant pre-trend nor any statistically significant coefficients in the after period (although there are many negative coefficients starting from the 7th month after the first warehouse). For non-storable crops, the entire negative effect on prices, seems to follow a general negative pre-trend from before the reform. Arrivals seem to present a similar positive trend, although here, again, all coefficients are not statistically significant.

[6] The is one negative and statistically significant negative coefficient 9 months prior to the first warehouse in the 60km boundary specification presented here, which is not statistically significant in both alternative 50km and 70km boundary specifications.

Figure 3: Event studies, mandi prices and arrivals



4.3 Seasonality

Figure 4 presents the month-dummy coefficients from the seasonality regressions, for the control and treatment markets and storable crops (Table 6 shows the respective regressions). For prices, we see a clear attenuation pattern (on average), when comparing the blue series (WDRA treated markets in the after periods) compared to the red series (control markets and treatment in the before periods). For arrivals we don't find a clear pattern of change in seasonality.

Table 5: Event studies, Mandi prices and arrivals

VARIABLES	(1) lprice, storable	(2) lprice, non-storable	(3) larrivals, storable	(4) larrivals, non-storable
-9	-0.025**	0.177***	0.200*	-0.785
	(0.0100)	(0.0610)	(0.1130)	(0.4920)
-8	-0.008	0.177***	0.036	-0.596
	(0.0100)	(0.0550)	(0.0970)	(0.4290)
-7	0.001	0.202***	-0.051	-0.536
	(0.0100)	(0.0500)	(0.0850)	(0.3720)
-6	-0.001	0.211***	-0.03	-0.407
	(0.0090)	(0.0410)	(0.0850)	(0.3140)
-5	-0.002	0.170***	-0.088	-0.363
	(0.0080)	(0.0340)	(0.0790)	(0.2520)
-4	0.004	0.124***	-0.056	-0.26
	(0.0070)	(0.0280)	(0.0710)	(0.1910)
-3	-0.01	0.080***	0.054	-0.117
	(0.0060)	(0.0210)	(0.0660)	(0.1310)
-2	-0.012*	0.054***	0.03	-0.089
	(0.0070)	(0.0120)	(0.0650)	(0.0730)
-1	0.002	-0.002	0.041	0.086
	(0.0050)	(0.0160)	(0.0560)	(0.0680)
0	-0.004	-0.028	0.015	0.138
	(0.0080)	(0.0240)	(0.0790)	(0.1300)
1	0.004	-0.02	0.065	0.234
	(0.0090)	(0.0300)	(0.0840)	(0.1880)
2	0.011	-0.049	0.106	0.371
	(0.0090)	(0.0380)	(0.0750)	(0.2510)
3	0.029***	-0.094**	0.082	0.441
	(0.0100)	(0.0430)	(0.0910)	(0.3130)
4	0.036***	-0.135***	-0.014	0.483
	(0.0120)	(0.0490)	(0.0960)	(0.3700)
5	0.043***	-0.187***	0.022	0.567
	(0.0110)	(0.0580)	(0.1020)	(0.4340)
6	0.035***	-0.235***	-0.171*	0.66
	(0.0130)	(0.0660)	(0.0950)	(0.4940)
7	0.033**	-0.244***	-0.135	0.729
	(0.0130)	(0.0720)	(0.1150)	(0.5570)
8	0.052***	-0.241***	0.041	0.782
	(0.0140)	(0.0790)	(0.1160)	(0.6180)
9	0.067***	-0.280***	-0.111	0.901
	(0.0170)	(0.0860)	(0.1210)	(0.6770)
10	0.072***	-0.276***	-0.059	0.916
	(0.0180)	(0.0940)	(0.1250)	(0.7370)
11	0.062***	-0.328***	-0.09	1.118
	(0.0170)	(0.1020)	(0.1270)	(0.8000)
12	0.061***	-0.375***	-0.01	1.222
	(0.0180)	(0.1080)	(0.1390)	(0.8590)
13	0.051***	-0.428***	-0.038	1.243
	(0.0190)	(0.1160)	(0.1440)	(0.9180)
Observations	30,819	28,022	30,827	28,022
R-squared	0.824	0.731	0.481	0.728
Fixed effects	Market, Crop	Market, Crop	Market, Crop	Market, Crop
	Month-Year	Month-Year	Month-Year	Month-Year

Treatment defined at the 60km boundary; Only states ever treated included and the years 2013-2018; Standard errors are clustered at the district level; $***p < 0.01$, $**p < 0.05$, $*p < 0.1$

Figure 4: Month coefficients for treatment and control groups, prices and arrivals

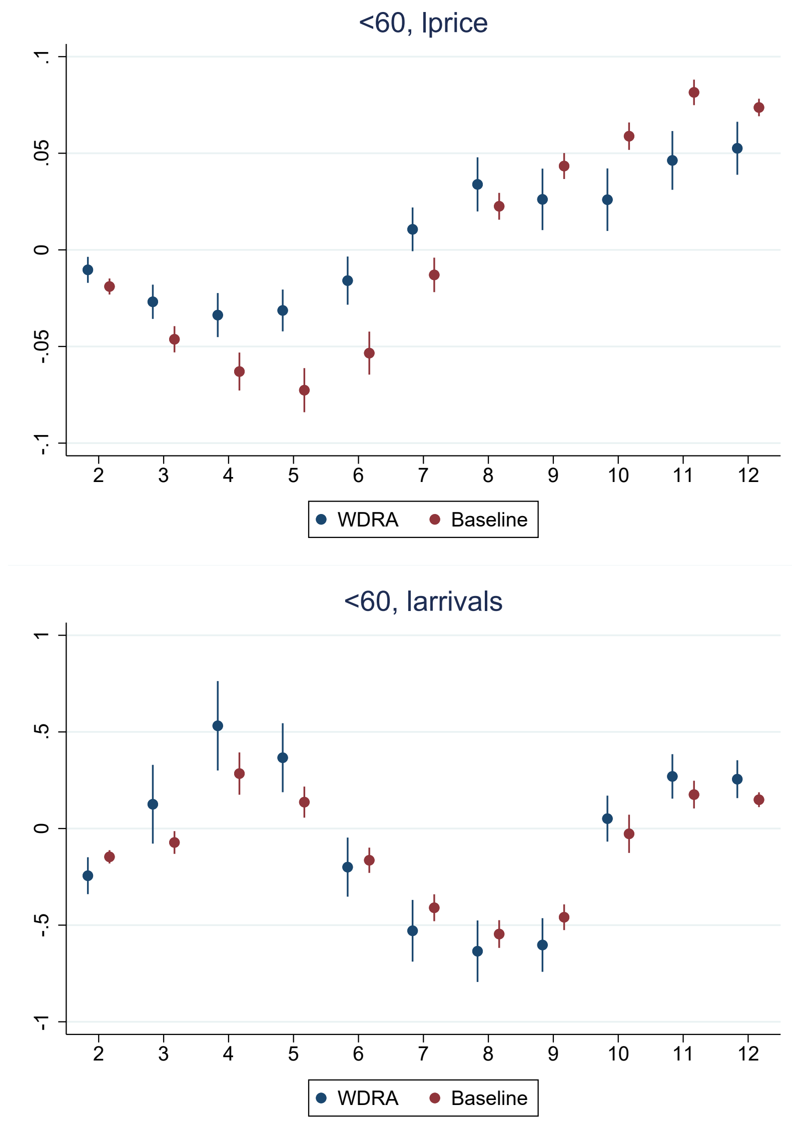


Table 6: Seasonality, prices and arrivals

VARIABLES	(1) Baseline lprice	(2) WDRA lprice	(3) Baseline larrivals	(4) WDRA larrivals
m2	-0.0189***	-0.0103***	-0.146***	-0.244***
	(0.002)	(0.003)	(0.018)	(0.049)
m3	-0.0463***	-0.0269***	-0.0722**	0.126
	(0.003)	(0.005)	(0.030)	(0.103)
m4	-0.0630***	-0.0337***	0.284***	0.532***
	(0.005)	(0.006)	(0.056)	(0.117)
m5	-0.0726***	-0.0313***	0.137***	0.367***
	(0.006)	(0.005)	(0.041)	(0.091)
m6	-0.0534***	-0.0159**	-0.164***	-0.200**
	(0.006)	(0.006)	(0.033)	(0.078)
m7	-0.0130***	0.0106*	-0.410***	-0.529***
	(0.005)	(0.006)	(0.036)	(0.081)
m8	0.0226***	0.0339***	-0.546***	-0.635***
	(0.004)	(0.007)	(0.037)	(0.081)
m9	0.0434***	0.0261***	-0.459***	-0.603***
	(0.003)	(0.008)	(0.034)	(0.071)
m10	0.0588***	0.0260***	-0.0273	0.0513
	(0.004)	(0.008)	(0.050)	(0.060)
m11	0.0815***	0.0463***	0.176***	0.270***
	(0.003)	(0.008)	(0.037)	(0.058)
m12	0.0737***	0.0526***	0.149***	0.255***
	(0.002)	(0.007)	(0.020)	(0.050)
Constant	7.214***	7.598***	4.755***	4.955***
	(0.002)	(0.004)	(0.024)	(0.048)
Observations	526,579	44,223	531,368	44,239
R-squared	0.722	0.763	0.402	0.43
Fixedeffects	Market, Crop Year	Market, Crop Year	Market, Crop Year	Market, Crop Year

Standard errors are clustered at the district level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

4.4 Entry

We briefly consider the determinants of entry by public and private warehouses into the different districts of India, and the effect of entry by an additional warehouse using the concept of entry threshold ratios (ETRs) (as in Bresnahan and Reiss (1991) and others). Table 7 presents the distribution of market structures of the two types of program warehouses. Out of the 595 district in the data, 476 have no WDRA warehouse in 2018 and the remaining 119 have at least one program warehouse. Out of those, only 12 districts have both private and public warehouses, so in most cases, the two types have entered different districts at this point in time. In total, 62 districts have one program warehouse, 25 have two and 6 have three.

Table 7: WDRA market structures

private/public	0	1	2	3	4+	Total
0	476	37	10	3	2	528
1	25	3	1	0	0	29
2	12	0	1	1	0	14
3	2	0	2	1	0	5
4+	16	2	0	0	1	19
Total	531	42	14	5	3	595

For the entry analysis we group the districts with four and more warehouses into one category. Since at this point competitive interaction between the two types of warehouses is rare within the same district, we look at their entry decisions separately rather than modeling their strategic interactions. A summary of the results of the two ordered-Probit regressions is presented in Table 8. We run the number of warehouses of a certain type in each district on a market size variable, the ln of total area of agricultural holdings in the district, and other district characteristics including the average holding size (ln), the size of literate rural population (ln), and the availability of different types of credit sources in the district.

Larger markets (in terms of agricultural area) experience increased entry by both private and public warehouses. Public warehouses also enter markets with larger holdings on average, so they potentially cater to larger farmers at the initially stage, while for the private warehouses this coefficient is negative and not statistically significant. The coefficient for the literate population is larger for public warehouses but not statistically significant in both cases. The availability of commercial banks seems to increase presence of public warehouses but not of private ones, and no positive effect on entry is found for cooperative credit sources (banks and credit societies).

The ordered-Probit cutoffs are higher for public warehouses suggesting that markets of the same population size are more profitable for private warehouses compared to the public ones. The ETRs which are calculated from these thresholds suggest that the entry of the second competitor in the private sector increases competition (the ETR is greater than one) but this effect is exhausted after the third entrant. For the public sector however, ETRs are larger than one and even increase with subsequent entry, suggesting that the fully competitive status is potentially not reached.

Table 8: WDRA entry ordered-Probit

VARIABLES	private	public
ln area of holdings	0.647***	0.701***
	(0.238)	(0.230)
ln ave. size of holdings	-0.0296	0.566**
	(0.264)	(0.274)
ln literate population	0.0198	0.496
	(0.328)	(0.361)
Agricultural credit societies	0.000319	-0.00240***
	(0.001)	(0.001)
Cooperative banks	0.00306	-0.00275
	(0.002)	(0.003)
Commercial banks	-0.00650*	0.0115***
	(0.004)	(0.004)
Cutoff 1	9.405***	16.94***
	(3.290)	(4.267)
Cutoff 2	9.876***	17.61***
	(3.294)	(4.280)
Cutoff 3	10.18***	18.20***
	(3.296)	(4.286)
Cutoff 4	10.29***	18.84***
	(3.296)	(4.297)
Observations	321	321
Log-Likelihood	-143.3	-124.9
s2/s1	1.035	1.301
	(0.020)	(0.012)
s3/s2	1.07	1.554
	(0.015)	(0.012)
s4/s3	0.879	1.86
	(0.008)	(0.017)

Standard errors in parentheses *** $p< 0.01$, ** $p< 0.05$, * $p< 0.1$

5 Conclusion

Post-harvest credit programs, especially when coupled with access to storage facilities are hoped to provide farmers more flexibility in choosing the timing of selling their crops, and increasing their bargaining power when facing traders in rural markets.

In this paper we presented an analysis of a warehouse receipt program in India, which was established in 2007 but began to gain momentum almost a decade later with program warehouses appearing in more and more Indian states. We studied how physical proximity between market places and new program warehouses affected prices and arrivals of storable and non-storable crops. For storable crops, the main focus of the program, we find a significant and persistent positive effect on prices obtained by the farmers for their crops. The seasonality analysis also shows an attenuation in the inter-seasonal price volatility in treated markets. For non-storable crops, any recorded changes in prices seem to relate to pre-treatment trends rather than being causaly related to the program.

For quantities arriving at markets, we do not find any significant change following the program. We also cannot detect a clear pattern of a change in seasonality in quantities. It is possible that changes in quantities arriving at markets were at a more granular frequency than months, or alternatively that the mere possibility to store crops in program warehouses improved some farmers' bargaining power without affecting actual quantities traded. This requires further investigation into finer frequency trading activity and supply response behavior by the farmers.

Analysing entry patterns by private and public warehouses at the initial stage of the program (until 2018) suggests that public warehouses entered larger markets compared the private ones, and markets with larger agricultural holdings, thus potentially catering to larger or wealthier farmers. Public warehouses also entered markets with higher availability of commercial credit sources, but a similar relationship was not found for private warehouses.[7] ETRs suggest that entry increases competition in both sectors, but the effect is exhausted in the case of the private sector after the third entrant, while for public warehouses, the effect is larger with each additional entrant.

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Table 9: Diff-in-Diff, Mandi prices

VARIABLES	(1) < 50km	(2) < 60km	(3) < 70km	(1) < 50km	(2) < 60km	(3) < 70km
WDRA×After	0.0239***	0.0193**	0.0189**	-0.0443**	-0.0474**	-0.0497***
	(0.00764)	(0.00762)	(0.00748)	(0.0204)	(0.0185)	(0.0180)
WDRA×After×Storable				0.120***	0.115***	0.119***
				(0.0295)	(0.0275)	(0.0266)
Combined effect for storable						
Observations	438,555	438,555	438,555	438,555	438,555	438,555
R-squared	0.6597	0.6596	0.6596	0.6603	0.6603	0.6605
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Crop FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors are clustered at the district level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Table 10: Diff-in-Diff, Mandi arrivals

VARIABLES	(1) < 50km	(2) < 60km	(3) < 70km	(1) < 50km	(2) < 60km	(3) < 70km
WDRA×After	-0.0394	-0.0205	-0.0141	-0.0810	-0.0374	-0.0297
	(0.0373)	(0.0373)	(0.0380)	(0.0692)	(0.0686)	(0.0674)
WDRA×After×Storable				0.0736	0.0290	0.0270
				(0.102)	(0.105)	(0.103)
Combined effect for storable						
Observations	439,408	439,408	439,408	439,408	439,408	439,408
R-squared	0.5301	0.5300	0.5300	0.5301	0.5301	0.5301
Market FE	Yes	Yes	Yes	Yes	Yes	Yes
Crop FE	Yes	Yes	Yes	Yes	Yes	Yes
Month-year FE	Yes	Yes	Yes	Yes	Yes	Yes

Standard errors are clustered at the district level; *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$

Figure 5: Event studies, mandi prices and arrivals

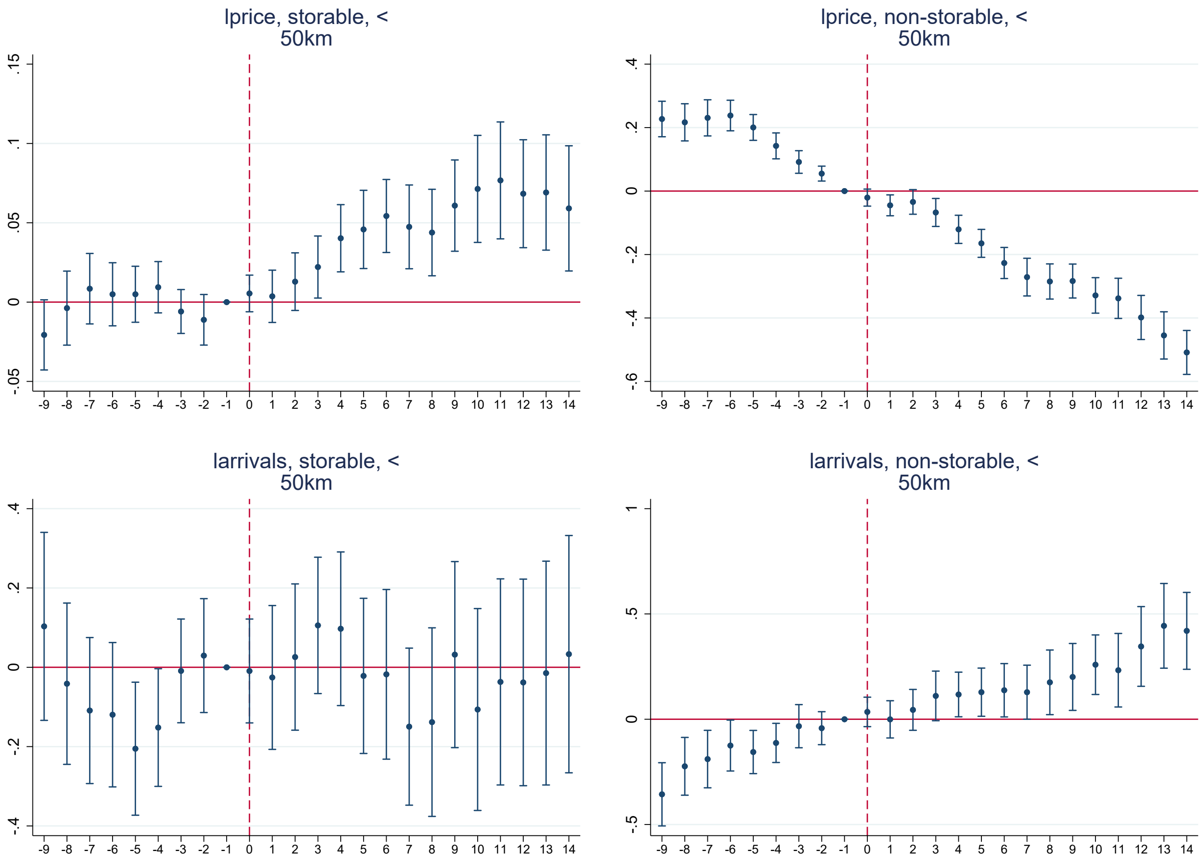

Figure 6: Event studies, mandi prices and arrivals