# Impact of India's demonetization on domestic agricultural markets

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#### Abstract

This paper examines the impact of an extreme monetary shock, India's demonetization event in 2016, on domestic agricultural trade. Using data on arrivals and prices from around 3000 regulated markets for 35 major crops, we find that demonetization reduced trade value by 13% in the short run, settling at 10% eight months after demonetization - driven more by a decline in prices than of arrivals. Triple difference estimates suggest that the impacts are sharpest for *kharif* /monsoon crops, perishables and crops where government intervention is minimal or absent; markets in areas with limited bank and market access fared worse. Our results suggest that demonetization left a lasting implosion of agricultural trade domestically.

 ${\bf Keywords}:$  demonetization, agricultural markets, difference-in-differences, triple differences, India

JEL Classification Codes : E5, E51, Q02, Q11, Q13

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## 1 Introduction

On November 8, 2016, the Government of India declared that two widely held denominations of the Indian Rupee - the Rs.500 and Rs.1000 notes - would cease to be legal tender after midnight.<sup>1</sup> In that one act, as much as 86% of the money in circulation was deemed illegal tender, engineering a currency squeeze that has few parallels elsewhere in recent times. In the days that followed, as people across the country deposited these two denominations in banks, the central bank of India began replacing these with new currency. By March 31, 2017, however, the value of currency in circulation was only 74% of that on the eve of demonetization (Figure 1). It took more than two years for the central bank to restore the currency in circulation back to its pre-demonetization levels. In scale and scope, the Indian experience of demonetization is perhaps larger and deeper than any other in recent recorded history.<sup>2</sup>

Demonetization was expected to have economy-wide impacts; it was anticipated that it would affect the informal sector and agriculture more, given their heavy reliance on cash for daily transactions. In this paper, we assess the impact of demonetization on trade in domestic agricultural markets. We focus on government regulated markets (or *mandis*), where typically farmers sell their produce to traders in a designated space. We estimate the value of domestic agricultural trade that was displaced on account of demonetization and examine the underlying drivers of these impacts - specifically, whether these impacts manifest via demand or supply factors.

Our motivation for investigating the impact on agricultural trade is manifold. We recognize that the impacts on agriculture trade and prices are at best intermediate, proxy indicators that fall short of estimating the welfare implications for farmers, in terms of either their incomes or expenditures. However, given that nationally representative data on farmer incomes are not routinely collected<sup>3</sup> and data from household expenditure surveys will likely take a while, the impacts on domestic agricultural trade offer the best proxy for farmer receipts. This is especially since most farmers do not stock or store most cash crops beyond a few weeks. Second, even with regard to impacts on transaction volumes and prices in the *mandis*, there has only been anecdotal evidence during the weeks following demonetization. Limited research based on secondary data remains equivocal. Some claimed, soon after demonetization, that trade would not be impacted since many transactions are checkbased and that fears of an implosion of agricultural trade domestically are exaggerated.<sup>4</sup> Others found that trade in these *mandis* reduced, at least in the immediate aftermath of

<sup>&</sup>lt;sup>1</sup>Circular Number RBI/2016-2017/122 DCM(plg)No.1226/10.27.00/2016-17 issued on November 8, 2016. See Reddy (2017); Ghosh et al. (2017) for accounts of demonetization.

 $<sup>^{2}</sup>$ Myanmar's demonetization in 1987 that invalidated 80% of the currency in circulation without a smooth transition is by far the most like the Indian experience.

<sup>&</sup>lt;sup>3</sup>National surveys of farmer incomes are available from the 70th and 59th Rounds, conducted by the National Sample Survey Organization in 2013 and 2003 respectively. There have been no other systematic data collection efforts to gauge farmer incomes in India thus far.

<sup>&</sup>lt;sup>4</sup>For example, see Reassessing the Impact of Demonetisation on Agriculture and Informal Sector, RACE, IDF, 2017 and Agricultural Growth after Demonetization, NITI Aayog blog series, 2017. Both these studies compare pre-post differences in *mandi* trade and prices from secondary sources, and argue that demonetization did not have an adverse impact.

demonetization.<sup>5</sup> Given these conflicting perspectives, our study aims to shed light on this debate using a larger coverage of crops, markets, time periods and appropriate identification strategies that support causal inference. Third, despite agriculture's declining importance as a contributor to GDP, accounting for 14.9% of the country's GDP, about half of all people derive livelihoods from agriculture (Government of India, 2016b). Agriculture is known to impact overall economic growth as a result, an observation made with predictable regularity in most discussions of economic growth in India. We can thus assess the slowdown in growth rates in India's Gross Domestic Product (GDP), in the quarters following demonetization, in light of the impacts on India's agricultural sector.

Our analysis also contributes to uncovering some understudied relationships between monetary policy and agriculture in developing and transition economies. India's demonetization was akin to a sudden, even if exceptional, monetary tightening by the central bank. That monetary policy can have significant impacts on (real) sectors that are not well integrated into the modern economy is an old concern (Chambers, 1984; Chambers and Just, 1982; Schuh, 1974). There have also been several historical studies on impacts of demonetization and monetary contraction (Hamilton, 1987; Miskimin, 1964; Ciriacy-Wantrup, 1940). Early theoretical work on the impacts of monetary policy emphasizes that it can have nonneutral effects on agriculture, with a restrictive policy depressing agricultural prices and incomes, at least in the short and medium run (Chambers, 1984; Frankel, 1986; Belongia, 1991; Ardeni and Freebairn, 2002; Frankel, 2008; Diaz-Bonilla and Robinson, 2010). Existing empirical literature assessing the relationship between monetary policy and commodity prices too mostly support these claims (Barnett et al., 1983; Frankel and Rose, 2010). Most of these more recent studies focus on the fallout of U.S. monetary policy shocks on commodity prices. There are as yet few contemporary studies from other countries, especially developing economies. Our paper contributes to this redressing this gap in the literature.

Identifying causal impacts of monetary policy is empirically challenging because monetary policy shocks could themselves be endogenous responses to commodity prices (Anzuini et al., 2013). For example, Bernanke et al. (1997) argue that positive oil price shocks induces a monetary policy response that can further amplify the effect of the oil price shock itself. In contrast, India's demonetization was not driven by general economic conditions and its stated objective was to rein in the black economy. The fully exogenous and unanticipated nature of the event offers greater scope to identify empirically the consequences of monetary contraction on the agricultural sector.<sup>6</sup>

Our paper adds to a small and growing body of works that analyze the consequences of India's demonetization. These include impacts on economic activity (Chodorow-Reich et al., 2018), employment and livelihood strategies (Dewan and Sehgal, 2019; Krishnan and Siegel, 2017) stock markets (Dharmapala and Khanna, 2018), digitization of financial transactions (Agarwal et al., 2018; Karmakar et al., 2018) and political outcomes (Bhavnani and Copelovitch, 2018; Banerjee et al., 2018). Chodorow-Reich et al. (2018) present a model

<sup>&</sup>lt;sup>5</sup>See Aggarwal, N and Narayanan S, "Demonetisation and agricultural markets", Ideas for India, 2016; and Banerjee, A and Kala, N, "The economic and political consequences of India's demonetisation", VoxDev Blogs, 2017. Banerjee and Kala, for example, report that sales of agricultural commodities was 83% of the predicted value.

<sup>&</sup>lt;sup>6</sup>As a coarse verification that this was indeed a surprise, we graph the trend in google search in English based on four variants of spelling (Figure 2).

#### Figure 1 Value of Notes in Circulation in India: July 2016 to June 30, 2017



Source: Reserve Bank of India. Table 2, Liabilities and Assets, Accessed March 31, 2018. The dashed vertical line is the date on which demonstration was announced. The second vertical line represents the date on which some of the withdrawal restrictions were eased for farmers and *mandi* traders. The last vertical dotted line represents the last date for legally depositing old currency notes in banks.

of demonetization to understand the importance of cash in facilitating transactions, and its consequences for real economic activity; they use data on variation in demonetization shock across different regions in India to show that it had an adverse impact on real economic activity. Dharmapala and Khanna (2018) analyze stock market's reaction to demonetization to determine the impact on the stated goals of demonetization, that is, tax evasion and corruption. While all these studies provide a macro-perspective on the impacts of the episode, our study, by analyzing the domestic agricultural markets in particular, provides a detailed analysis of the impacts at a more micro-level.

We use data on arrivals and prices from 2953 regulated markets in India for 35 major agricultural commodities for the period 2011-2017. These 35 commodities account for an overwhelming share of land under cultivation and value of production and are hence representative of Indian agriculture in more than one sense. The specific challenge of attributing causal impacts to demonetization is the absence of an obvious counterfactual since the policy was implemented countrywide. Reflexive comparisons before and after demonstration do not work since the post-treatment period coincides with a routine tapering off of the harvest season, when *mandi*-based trade declines for many commodities. We navigate this difficulty by choosing earlier years as counterfactuals for 2016-17, i.e., 2016-17 serves as the "treatment" unit/ year and 2011-16 as comparison years; we use the date, November 8th, to partition pre-treatment and post-treatment time periods. Our empirical strategy involves the use of a difference-in-differences (DD) technique, but we frame our difference-in-differences in time-time space rather than state-time space. We assess impacts for varying windows after demonetization and find that demonetization displaced domestic agricultural trade in regulated markets over 13% in the short run settling at almost 10% even after the end of the 8 months (233 days) after demonetization.<sup>7</sup> We find that most of this decline is on account of

<sup>&</sup>lt;sup>7</sup>Our other models with alternate specifications predict similar impacts of around 13-14% settling to







the significant decline in prices rather than of arrivals, which appear to have recovered over a period of three months. Specific crop groups and geographies drive these results. We uncover the heterogeneity of impacts across *mandis* and crop types using a set of commoditywise DD models and a set of triple differences (TD) models, described later in the paper. The TD models help identify impacts for perishable crops, monsoon crops - whose harvests coincide with the time of demonetization and for *mandis* in areas with relatively better financial and market access, and proximity to urban centres. Overall, the negative impacts are largest for *kharif* or monsoon crops that had just been harvested when demonetization occurred, in commodities where government intervention is minimal and for perishables, where farmers did not have the choice to store in anticipation of better prices. The impacts are the least for crops where governments actively procure, for *rabi* winter crops that would come to the market only months after demonetization and for non-perishables. Trade in perishables was displaced to the extent of 17% more than for non-perishables a month after demonetization. It recovered, but not fully, over the 8 months that followed. We find, as expected, most of this decline in value of perishables came from decline in prices, the most compelling evidence of the impact on farmers' incomes.

We also find as expected that *mandis* in district with better access to bank branches saw more muted impacts relative to those with poorer access to cash; access to Automated Teller Machines (ATMs) do not seem to have made a difference. Smaller *mandis* and *mandis* in districts with higher market density also appear to have lower impacts than larger *mandis* and those in districts with fewer *mandis*, respectively. Farmers in districts with a dense network of *mandis* were perhaps on average close enough to smaller *mandis*, at least in the short run. Smaller *mandis* seem to have crowded in trade relative to the larger mandis briefly but at the end of eight months after demonetization, there was no difference. *Mandis* in districts with cities over one million, however, did worse than those in more rural districts. All of these impacts conform accounts from that time. Robustness checks and falsification tests largely support our findings that the impacts we identify are most likely due to demonetization.

The paper is organized into six sections. Following this discussion, we describe the context

around 11-12% by the end of 90 days.

of domestic agricultural trade in India. We then conceptualize the pathways through which demonetization is expected to impact domestic agricultural trade. Section 3 discusses the data used and empirical strategy. Section 4 discusses the results, with Section 5 devoted to checking the robustness of results. Section 6 summarizes these results and discusses some of the coping strategies farmers used in the immediate aftermath of demonetization.

## 2 The context of agricultural transactions in India

Domestic agricultural trade in India typically occurs in designated markets declared under the Agricultural Produce Marketing Committee Act (APMC Act). Historically, farmers were mandated to sell in these markets to licensed intermediaries. Although several states have reformed this law allowing private trade, contract farming and direct procurement, for most commodities a significant proportion of trade passes through these *mandis*, even if the first trade might be a sale by a farmer to an itinerant trader or within the village. In a typical process at a regulated *mandi*, a farmer brings his/her produce to the *mandi*, takes it to the commission agent of his /her choice, unloads the produce in the agent's premises (Aggarwal et al., 2017). Bidding take place for each lot, which gets a unique identification number. During the designated trading hours, prospective buyers, including traders and processors, each of whom holds a licence to trade in the specific *mandi*, visits the agent's premises, examines the quality of the produce and quotes a bid price. The bidding is either closed tender - the bid is private and written down on a paper slip or on a computer - or it is through an open-cry auction. The former system dominates for commodities that see large daily arrivals. At the end of the trading window, the highest bid price is declared as the winning bid. The farmer has the right to reject the bid; in this case, his/her lot is placed for bidding on the next trading day in the *mandi*. If the farmer accepts the price, the produce is weighed and a sales bill is generated. The trader pays the commission agent, who, after deducting his/her commission and the *mandi* fee, pays the farmer, usually in cash. Traders typically do not pay the commission agents immediately and instead buy on credit, while the payment is settled anytime between fifteen days to six months after the transaction. The commission agent however pays the farmer, at the time of the transaction or within one or two days, after deducting any interest for or repayments against loans that (s)he may have provided to the farmer in the past.

Virtually all of these transactions are cash-based. Although check payments and direct bank transfers are increasingly being used by processors, this still forms a small portion of transactions (Aggarwal et al., 2017). As of 2015, there were 6746 such regulated markets (2479 of them termed primary markets and the rest called submarket yards or minor markets), with each district in the country having at least one such market (Government of India, 2016b).<sup>8</sup> The context we study therefore involves a large number of heterogeneous markets - in terms of size, commodities traded, location and so on. Different states allow private markets direct trade outside the *mandi* regularly. Despite heterogeneity and the existence of credit relations that are long-term relationships, cash transactions dominate *mandi*-based trade and the *mandi* is a key channel for a bulk of the produce.

 $<sup>^{8}</sup>$  There are also a reported 26519 rural markets - primary and wholes ale that are not regulated Government of India (2016b).

### 2.1 Conceptual Pathways and Hypotheses

What is the likely impact of demonetization on domestic agricultural markets, as represented by *mandi*-based trade? We expect that a shared shortage of liquidity reduces demand for commodities because commission agents and traders are unable to pay the farmers in cash. The traders themselves may face a demand shock if their buyers are also cash-constrained or are only willing to purchase on credit or bank-based payments. In the latter case, traders and commission agents might still face a cash constraint because even with banks, access to liquidity was restricted.<sup>9</sup> Our own field visits to prosperous regions near the national capital revealed that even with a high number of bank branches and ATMs in the town, there was a shortage of cash.<sup>10</sup> These factors together would shift the demand curve inwards reducing the quantity traded as well as the price.

From the supply side, most farmers in India typically sell their cropsimmediately after harvest due to liquidity constraints. It is however possible that with demonetization, farmers held back their produce from sale, anticipating a collapse in demand and consequent low prices. Alternatively, the transactions costs (labour and transportation) of bringing the produce to *mandis* could result in farmers postponing their journey to the market, potentially overriding an urgent need to sell produce for cash.<sup>11</sup> Either or both of these has the effect of contracting supply in the *mandis*, resulting in lower traded quantity and higher price.

The net effect would depend upon which factor dominates. We posit the following hypotheses:

- With a contraction of both demand and supply we would expect the volumes of *mandi* trade to decline, especially for non-perishable commodities where the farmer might store it and sell at a future date. This may not happen for perishables, where storing is not an option available to the farmer. Nor would one expect strong impacts for commodities that either see government procurement<sup>12</sup> or are vertically coordinated and where transactions are based on contracts, rather than spot markets.
- The prediction for prices is less obvious. If as described above, both demand and supply contract, then the impact on prices depends on which effect is stronger given their relative elasticities. In some cases, especially for perishables, where storing the commodity is not an option, or if the farmer is in an urgent need of the money, there

<sup>&</sup>lt;sup>9</sup>For instance, post-demonetization, cooperative banks, a key rural financial institution, were not allowed to accept deposits of old currency, even in exchange for new currency. Withdrawal and exchange limits on new currency were in force for weeks after demonetization (Appendix A online). It was not until November 21, 2016that farmers were granted some latitude to withdraw upto Rs.25000 per week in cash from specific deposit accounts. Traders registered with APMC markets / mandis were allowed to withdraw, in cash, Rs 50,000/- in a week with some conditions (Figure 1).Loans for the following cropping season were permitted around the same time. The new currency notes were slow to reach rural areas and access to cash through ATM and banks was not easy. Further, old ATMs had to be recalibrated to dispense new notes that were smaller than the notes that were banned.

<sup>&</sup>lt;sup>10</sup>These field visits were to regulated markets in Gannaur (Haryana) and Azadpur (Delhi) during November 29-December 1, 2016. Field visits involving conversations with farmers included Karnataka in June and July, 2017; Madhya Pradesh, March, 2017 and Tamil Nadu, March 2017.

<sup>&</sup>lt;sup>11</sup>We expect that this latter effect would be weak given the shared scarcity of cash.

<sup>&</sup>lt;sup>12</sup>See "No demonetisation impact on FCI, rice procurement soars 17%", Financial Express, January 6, 2017, accessed on December 1, 2018.

would be a decline in the prices. Consumers might change their consumption pattern or reallocate expenditures within food groups, in the context of a cash crunch, away from relatively more expensive to less expensive foods. The net impact is not immediately obvious and would vary across commodities, the nature of government intervention and market structure for each commodity.

We examine *mandi* arrivals and prices to understand which effect dominates in the impacts we see on total value of domestic agricultural trade.

We also anticipate heterogenous impacts on total value of trade, and on arrivals and prices across *mandis*. Our hypothesis is that *mandis* that have limited penetration of banks and are relatively less connected to urban areas are likely to be more affected. According to the Report of the Committee on Medium-term Path on Financial inclusion, in June 2015, the number of branches per 100,000 of population in rural and semi-urban areas in India was 7.8, less than half the number in the urban and metropolitan areas (18.7). The median global value as per the data from the World Bank in 2015 was 12.62.<sup>13</sup> It could also be the case that farmers don't simply choose whether or not to sell in the *mandi* but pick the *mandi* they wish to go to. Our field visits in the aftermath of demonetization suggest that some farmers coped with the cash constraints by choosing to sell in nearer, rather than their preferred distant *mandis*. This diversion of trade to *mandis* closer to the point of production could imply that smaller *mandis* closer to production centres saw lower decline in arrivals relative to larger *mandis*. At the same time, the farmer might associate larger *mandis*.

There are several reasons, however, that an anticipated implosion of agricultural markets might not occur, especially with respect to arrivals. Many creative ways to circumvent the ban surfaced in the weeks after demonetization. For example, our field visits revealed that in many *mandis*, despite the ban, old currency continued to be accepted for payment at a discount. Across *mandis*, a sophisticated schedule of prices for produce had developed depending on whether one was trading in new or the old illegal currency.<sup>14</sup> There were also reports that consequently those who had stashes of old currency, possibly black money, were buying up agricultural produce rather than deposit these in banks.<sup>15</sup> Most often however, we found that goods were passing through but not money, so that farmers, agents and traders were transacting on credit.<sup>16</sup> Sometimes multilateral arrangements had evolved where farmer bought inputs for the impending agricultural sowing from family members of traders who they had just sold to on credit, thus settling the transaction in kind. In each of these cases, one would not expect to see a sharp impact on arrivals. In these cases, the impact of demonetization is likely on consumption and savings.<sup>17</sup>

<sup>&</sup>lt;sup>13</sup> The World Bank, World Development Indicators, accessed on November 1, 2017.

<sup>&</sup>lt;sup>14</sup>See for example, Krishnamurthy, M, "Trading Notes", Hot Spots, Cultural Anthropology, 2017.

<sup>&</sup>lt;sup>15</sup>Paddy mandi a green pasture for black money hoarders, The New Indian Express, November 22, 2016, last accessed on November 2, 2017.

<sup>&</sup>lt;sup>16</sup>See for example, At Delhi's Azadpur mandi, Lack of Money is Slowly Choking Business and Also Workers, The Wire, November 18, 2016, last accessed on November 2, 2017.

<sup>&</sup>lt;sup>17</sup>Our fieldwork also indicated that the persons who were likely most affected were the farm workers and their families, who had not been paid wages since the farmer had no cash. For this group, remittances home had dried up and farm workers reported that they had cut back food consumption too to keep afloat. See: Jobless, these labourers can barely get one meal a day, The Economic Times, December 11, 2016, last

Likewise if successive notifications easing restrictions on access to new currency were truly releasing constraints on cash, we would see a muted impact on average or a tapering off of negative impacts, if any.<sup>18</sup> These also include innovative solutions by state governments. For example, in the southern state of Telangana, the government, along with a bank, issued coupons to trade in farmers' markets that could later be encashed. In Tamil Nadu, temples under the state government opened up their cash donation boxes containing offerings made by pilgrims to exchange banned tender.<sup>19</sup> All or any of these factors would mitigate the negative impacts of demonetization. We also believe that if itinerant small traders who pick up produce at the farmgate were themselves cash starved, we might actually witness trade that would have otherwise occurred locally within the village, making its way to the *mandis*, where perhaps the likelihood of finding a buyer is higher. In effect, the actual impact of demonetization on domestic agricultural trade is an empirical question.

## 3 Data and Empirical Strategy

### 3.1 Data

For the analysis, we choose 35 commodities that represent each of about twelve commodity groups identified by the Ministry of Agriculture.<sup>20</sup> The choice of these crops is based on the cultivated (gross/net) area with each commodity group in 2015, although we have taken care that these broadly reflect the shares over the period 2012-2017 (See Table 1). We are therefore able to account for commodities that reflect Indian agriculture broadly. For foodgrains (i.e., cereals and pulses), the crops we consider account for 85% of land under foodgrains, for oilseeds, the proportion is 87% and for horticulture (fruits, vegetables, aromatic plants, plantation crops and spices), the commodities included account for close to 60% of the total area under such crops.<sup>21</sup>

Not all of these commodities are produced in all the states or in all seasons. Our list of crops include *kharif* or monsoon crops, that were either being harvested or were ready for harvest at the time of demonetization. The typical *kharif* crop involves sowing in June and harvests ranging from October to January depending on the crop and the varieties. Our

accessed on November 2, 2017.

<sup>&</sup>lt;sup>18</sup>See for example, the following reports, *Demonetisation: Govt relaxes rules, allows farmers to use Rs.500* notes to buy seeds, Business Standard, November 21, 2016, last accessed on November 2, 2017 and *Further* demonetisation relaxation likely for farm sector, weddings, Business-Standard, November 23, 2016, last accessed on November 2, 2017.

<sup>&</sup>lt;sup>19</sup>See for example, Temple donations in TN see slump post demonetisation, The New Indian Express, November 19, 2016, last accessed on November 2, 2017. and Telangana govt has a creative solution for farmers' market in demonetisation woes, The News Minute, November 19, 2016, last accessed on November 2, 2017.

 $<sup>^{20}</sup>$ Commodities are grouped into cereals, pulses, oilseeds, fibres, sugar and beet, plantation crops, spices, fruits, vegetables, flowers, aromatic crops and honey. Livestock products are considered separate from "crops" and are excluded from the analysis. While live animals are traded in *mandis*, livestock products are not.

 $<sup>^{21}</sup>$ It is difficult to get an estimate of the selected commodities' contribution to the value of production of all crops, without also selecting a set of prices that represent a normal year. We therefore use acreage as the criterion.

focus on *kharif* crops is because we expect that demonetization would mainly impact these and not those that are typically grown in other seasons. The other important seasons are *rabi* (winter) and summer. *Rabi* sowing typically runs from November to February or March and summer between February and June.We use crop year rather than calendar or financial years. Crop years run from July in each year to June the following year. We use data spanning the crop years 2012 to 2017, where crop year refers to the period July to June. Our choice of years is to ensure that the set of regulated markets is uniform. A longer time span would pick up variations in reporting, neglect newer markets and include markets that were either merged with others or ceased to function. In aggregate, we analyze 35 commodities spanned across commodity groups of cereals, pulses, oilseeds, spices, plantation, sugar, fibre. We include vegetables and fruits to examine the impact on perishable commodities.

For these selected crops, we analyze arrivals across all regulated *mandis* in the country. These data are reported daily for each trading day. Arrivals typically refer to those lots for which official gate entry has been made. These data for arrivals cannot be construed as representing all trade for two reasons. In several states, reforms of the APMC Act allow direct transactions between farmer and retailer/processor/consumer. Crops such as sugarcane for example are delivered to sugarcane factories and increasingly crops such as cotton are delivered directly to ginning, pressing units and mills, groundnut to decortication units and so on. These lots would not therefore pass through a *mandi*. Second, despite the mandate for commodities to be trading in these regulated markets, for a number of commodities in a number of locations, trade is known to occur outside the *mandi*, that often goes unrecorded in order to avoid payment of *mandi* fees and taxes. These caveats aside, nationally representative surveys of agricultural households suggest that the transactions involving direct sale to processors is fairly limited except for a few commodities.

We source our data from the Ministry of Agriculture, Government of India. The data reported include daily arrivals and prices. We accessed these data at different points in time allowing for enough time for these data to be complete. We also conducted random checks at the time of analyzing to ensure that the data we used did not change over time, owing to fixing errors, updations, etc.<sup>22</sup> We treat each unique *mandi* name as separate. Each APMC market might have associated sub-yards or sub-markets and sometimes the parent APMC reports data collated from all its sub-mandis. We do not attempt to combine or split these data and retain the original form in which data are available. Further, arrivals are reported at the commodity level, so that it is impossible to identify how much of each variety of the commodity arrives. Three prices are reported - the minimum price at which a lot is traded, the maximum price as well as the modal transactions price. In our experience, the modal price is more a ballpark estimate than the actual mode. These prices are collected by mandi officials who physically circulate in the market multiple times during trading hours to record these in consultation with the agents and traders. In rare cases, it is recorded as the most frequently traded price based on the prices of each lot. In some markets, it is recorded as a linear combination of maximum and minimum, and is mode only in name. In contrast to arrivals, prices are, more often than not, documented for different varieties separately, although in practice we found that the category "Others" was often chosen as the default

<sup>&</sup>lt;sup>22</sup>We downloaded the data at four points of time - end-November 2016, end-December 2016, mid-January 2017, mid-March 2017 and mid-August 2017.



Figure 3 Marketing channels for *kharif* crops, 2012-13.

even when the variety was clearly distinguishable.

We use all data for the selected commodities, including all varieties reported. We use the minimum prices since it systematically and reliably records the lowest price of the day, though we also estimate our models using modal and maximum prices to check the sensitivity of results.<sup>23</sup> In our knowledge, ours is the first study which conducts a detailed analysis of government regulated agricultural *mandis* using the price and arrivals data at daily level. Goyal (2010) used monthly data on soyabean to analyse the impact of a change in the procurement strategy of a private buyer on the functioning of rural markets in India.

Table 1 presents percentage of arrivals during the *kharif* season for each selected commodity and the average number of *mandis* that reported arrivals during 2012-16. .Commodities such as paddy, maize, soyabean, cotton are primarily grown as *kharif* crops. The major *rabi* crops include wheat, cumin and Bengal gram. Arrivals for cereals such as paddy, wheat, maize, bajra soyabean, and pulses, including tur and Bengal gram, are reported by a large set of *mandis*. Within perishables, we see a large number of *mandis* reporting arrivals for onion, potato, tomato and brinjal. A smaller number of *mandis* report arrivals for the fruits, spices and plantation crops analyzed in the study. As discussed in Section 2, not all agricultural produce pass through *mandis* (Figure 3). Some of it is directly sold to co-operatives and government agency, mills and processors and to private traders through contracts.<sup>24</sup>

Commodities such as wheat, maize, bajra (peal millet), tur (pigeonpea) and Bengal gram (chickpea) have a large share of production that is sold via *mandis*. Others such as ragi (finger millet), jowar (sorghum), groundnut, soyabean have a much smaller share.<sup>25</sup> Figure 4 illustrates weekly arrivals for six selected commodities for three of the crop years analyzed.

 $<sup>^{23}</sup>$ We caution that our data are not transaction-level data, and to that extent, provide us an indicative value of the impact of the event on *mandi* trade. The use of minimum price also ensures that we do not over estimate the impacts.

<sup>&</sup>lt;sup>24</sup>The 70th Round of the National Sample Survey conducted in 2012-13 offers the best estimates of marketing channels for commodities that is nationally representative of agricultural households in India. Figure 3 shows the commodity wise share transacted via different channels by the farmer. Several trades that occur through private buyers who are typically itinerant vendors who visit the village also pass through *mandis* where the produce is aggregated and sold onward.

 $<sup>^{25}</sup>$ As mentioned earlier, soyabean and groundnut are often bought by processors. Ragi and jowar typically grown by poorer farmers and are sold within the village.

The shaded region in the graph indicates the *kharif* season, the period that was hit by demonetization (Week 18-19). For non-perishables, arrivals are uneven throughout the year. The peak season for paddy, soyabean and cotton is the *kharif* season. Tur harvests typically arrive between December to January. In contrast, arrivals for perishables such as tomato and banana are spread throughout the year. Thus, at least for some major commodities, a pre-post comparison in value of trade would not make sense, given the intra-seasonal patterns of arrival.

#### 3.2 Empirical strategy

#### 3.2.1 Difference-in-Differences

Our main empirical strategy is a Differences-in-Differences (DD) regression framework to analyze the impact of demonetization. We define the event of demonetization as the treatment, the crop year, 2017 as the treatment unit, and the preceding five years, 2012-2016 as the comparison units. The period before (after) November 8 in each crop year represents the pre (post)-treatment variable. Thus, we have one treated year, and five comparison years (2011-12 to 2015-16). We then use the days before (after) November 8 in each year as the pre(post)-treatment variable. We therefore apply the DD technique to time-time space rather than the customary state-time space.<sup>26</sup> This approach enables us to distill the effect of intra-year variation in the outcome of interest and is similar to the seasonal adjustment used in time series analysis.

We analyze the impact on total value of trade (computed as the product of the minimum price and arrivals) at a *mandi* for each commodity on a day using the following regression equation:

$$\ln V_{c,m,t} = \alpha_0 + \alpha_1 D_{post-Nov8,t} + \alpha_2 D_{2016,t} + \alpha_3 D_{post-Nov8,t} \times D_{2016,t} + \zeta X_{m,t} + \epsilon_{c,m,t}$$
(1)

where  $\ln V_{c,m,t}$  represents logarithm of daily value of arrivals for commodity, c, traded in mandi, m, on date, t.  $D_{2016,t}$  is a dummy that takes value one for the year 2016-17, and zero otherwise.  $D_{post-Nov8,t}$  takes value one for days from November 9 to July 31 in a year, zero otherwise.  $\alpha_1$  measures the difference on average between post-November 8 arrivals value relative to pre-November 8 arrivals value. This controls for the trend in arrivals value over the season, which ensures that the impact is not contaminated by an underlying intra-season trend in arrivals pre and post demonetization. The coefficient  $\alpha_2$  measures the average daily arrivals value for 2016-17 relative to other years. If for example, the year 2016-17 saw a bumper harvest or a greater area was devoted to a particular crop, translating into greater production and hence larger arrivals, one would expect arrivals (and thus their value) to be higher on average than in previous years. This is especially important in the context of

 $<sup>^{26}</sup>$ We prefer this innovation to using a predictive model because we believe the predicted values are associated with large errors. A related issue is that predicted values using rain might be irrelevant for irrigated agriculture. Likewise, the predictions of arrivals, even in rainfed areas, may depend more on the timing of onset of the monsoon and this could vary from year to year. Further, produce often travels long distances and across multiple states. In these instances, rainfall in the district where the *mandi* is located has limited bearing on arrivals; rainfall in the production sheds are more likely to matter.



Figure 4 Weekly arrivals for sample commodities

*Notes*: The graphs show weekly arrivals for six commodities belonging to each commodity group for three crop years analyzed in the study. Weekly arrivals are computed as sum total of arrivals for a commodity in a week across all *mandis* within a crop year. Week 18-19 represent the week in which demonetization was announced in 2016-17. The shaded region represents the *kharif* season which spans from October to January. The x-axis shows the corresponding week in a crop year.

demonetization, since 2016-17 coincided with a good agricultural season in terms of adequate rains, leading to bumper harvests for many commodities. Many observers have commented that the price declines observed could well be due to the high supply this year. Further, estimates of productionin 2016-17 suggests that it is in fact true for at least a few os the commodities studied (Table 2). X's indicate control variables discussed later in this section. The estimate from this model is the best proxy for value of trade displaced (or decline) domestically in the *mandis* and is therefore central to our analysis.

In all the regressions, we use *mandi* fixed effects to remove time invariant characteristics of *mandis*. Agricultural policy in India is a state subject, and several ongoing market reform initiatives could influence agricultural marketing transactions. We therefore include interactions between year and states as controls in part to account for these differential trends in all our pooled regressions. These state-year interactions would also pick up variations in production patterns across states and years. In addition, we also include year-month interaction effects. This controls for specific patterns of imports and exports, especially in crops where the government manages much of the external trade. It would also control for other macroeconomic factors (including the scale of replenishment of currency post-demonetization).

We control for day-of-the-week effects, to account for *mandi* trading days and trade diversion effects between *mandis* since different *mandis* might have different holidays. Our preferred model includes data for the full year, notwithstanding the fact that the crops may grow only in a particular season and most of it is marketed within a span of 3-4 months. We use dummy variables for each month to capture the variations in arrivals across months. Month and day effects also take care of variation in number of *mandis* reporting the data. For all models, we trim 0.05% of the data; we compute robust standard errors. One potential problem is the possibility of serial correlation, which could lead to wrong inferences (Bertrand et al., 2004; Angrist and Pischke, 2008). In an alternate version not presented here, we cluster the errors by *mandi*-crop, the results don't change.

In addition, we include a dummy variable to capture the effect of various festivals since they have a direct impact on the volume of arrivals and prices. For example, Diwali is an important festival celebrated across India. The date of the festival, determined based on the traditional lunar calendar, falls in the month of October or November and varies from year to year. To the extent that in the period of our analysis, it straddles pre and postdemonetization dates (November 8) in different years, this could confound the identification of our estimates. In most of the years in our sample period, the Diwali date was very close to the date on which demonetization was announced.<sup>27</sup> Our analysis of *mandi* trading patterns around Diwali indicates that arrivals start falling two days prior Diwali, and pick up after two days of Diwali (see Figure 5). Thus, we control for this effect by including a festival dummy which takes value one for the period of two days pre and post Diwali, zero otherwise. The festival dummy takes one and zero values around all the other festivals as well. We do not distinguish across these festivals to remove the chances of any bias that may result from our subjective judgement on the effect of each festival. We also control for the possible effect of national holidays<sup>28</sup> by including a holiday dummy that takes value one on these days, and

<sup>&</sup>lt;sup>27</sup>During our sample period, the festival of Diwali was on the following dates: November 26, 2011; November 13, 2012; November 3, 2013; October 24, 2014; November 11, 2015; and October 30, 2016.

 $<sup>^{28}</sup>$ India has three national holidays: 26<sup>th</sup> January (Republic day), 15<sup>th</sup> August (Independence day), and 2<sup>nd</sup> October (Mahatma Gandhi Jayanti).

![](_page_14_Figure_0.jpeg)

Figure 5 Diwali analysis for a few sample commodities

*Notes*: The graphs show event-study analysis 15 days pre and post Diwali. The bold blue line indicates the mean of arrivals during 2011-12 to 2015-16. The upper dashed blue line indicates the maximum arrivals in any of the years around Diwali, while the lower dashed line indicates the minimum arrivals. The black dashed vertical line indicates the Diwali day. The x-axis shows days spanning 15 days before Diwali to 15 days post Diwali. We exclude the crop year 2016-17 from this analysis.

zero otherwise.

Finally, we control for rainfall in all our regression specifications. Rainfall is measured monthly at the district level. We map all *mandis* studied here to their corresponding districts. We compute rainfall deficit or surplus as the difference between rainfall in a particular month and its historical average in that month over the past ten years. This is normalized using the standard deviation of the historical 10-year rainfall data for that month. We use these positive (and negative) normalized deviation of rainfall as two separate variables to account for the differential effect of surplus or deficient rainfall. We include twelve lags of rainfall data in the specification, to capture the entire cropping season that might potentially affect production, yield and marketed surplus. We particularly care that the pattern of arrivals across control and treatment years might vary based on the rains, since the latter overwhelmingly determine sowing and harvest dates. Controlling for lagged rainfall measures of varying lengths accounts for these differences.

We implement the DD analysis using varying windows after demonetization in order to understand whether the impacts are transient or not and to track the strength of the impact of demonetization over time. The variation in impacts over time is likely to arise because of two key factors, as mentioned earlier. First, the government took several measures to ease the difficulties farmers were facing as new currency was replenished (as shown in Figure 1 and Appendix A). These involved setting higher withdrawal limits for farmers and traders and enabling cooperative banks in rural areas to transact, among other things. Second, it is possible that farmers have limited capacity or ability to store and were only able to hold out for a short time after which they would bring it to *mandis* for sale even if the prices were low and their own circumstances challenging. We estimate the model for different windows around the event, starting with a comparison of one day after to 233 days after, until June 30, 2017, eight months after demonetization.

The identification strategy in this study is predicated on the assumption of parallel trends (i.e., time-invariant unobservable differences across comparison and treatment groups). This implies that in the absence of treatment, the treated unit and control units would have shared a similar trend. We check this by plotting mean pattern of cumulated arrivals and cumulated value of traded for control years vis-a-vis the pattern in the treatment year. Figure 6 shows the graph for the two variables aggregated across sample commodities and all mandis.<sup>29</sup> We see that the arrivals as well as the total value of trade follow a similar trend for the treated and control years, for most of the pre-November 8 period. Nevertheless, our month-year interactions take into account the possibility of time-varying trends across the comparison and treatment years.

We also check for any unusual dips or spikes prior to demonetization and account for the festival effects to control for Diwali that fell on October 30 in 2016. We believe that other than the festival, which we control for, the pre-treatment dip is largely irrelevant because the announcement of withdrawal of currency came as a surprise. The announcement came at 8 p.m. with currency remaining legal tender until midnight that day(Figure 2 earlier). Given that this is not a window for business in agricultural markets it is unlikely that there was transaction activity in anticipation of the change.

<sup>&</sup>lt;sup>29</sup>The blips in the two graphs for the treatment year correspond to Sundays, when most of the mandis are closed for trading.

Figure 6 Cumulated arrivals and value of trade aggregated across all sample commodities and mandis for control and treated year

![](_page_16_Figure_1.jpeg)

*Notes:* The graphs show the mean patterns of cumulated arrivals and cumulated value of trade for control years vis-a-vis the pattern in treatment year across all commodities and all *mandis*. We use the mean value of the cumulated arrivals and value of trade for the control years.

#### 3.3 Triple difference

In Section 2.1, we highlighted that impacts on domestic agricultural trade are likely to differ across commodities as well as *mandis*. A set of triple-difference regressions aim to capture these impacts. The generic specification to estimate the impact on total value of trade  $(V_{c,m,t})$  is given as:

$$\ln V_{c,m,t} = \alpha_0 + \alpha_1 D_{post-Nov8,t} + \alpha_2 D_{2016,t} + \alpha_3 D_{post-Nov8,t} \times D_{2016,t} + \alpha_4 D_{het-impact,c/m} + \alpha_5 D_{2016,t} \times D_{het-impact,c/m} + \alpha_6 D_{post-Nov8} \times D_{het-impact,c/m} + \alpha_7 D_{post-Nov8,t} \times D_{2016,t} \times D_{het-impact,c/m} + \zeta X_{m,t} + \epsilon_{c,m,t}$$

$$(2)$$

 $D_{het-impact,c/m}$  is a dummy that takes value one for the heterogenous effect that we want to analyze, zero otherwise. The coefficient associated with the third level interaction term,  $\alpha_7$ , captures the magnitude of the heterogenous or differential impact.

To isolate the differential impacts on perishables, relative to non-perishables, we define the variable  $D_{het-impact,c/m}$  as one for perishables and zero for non-perishables. Similarly, to analyze the impact on *kharif* crops relative to *rabi*, we allocate one and zero values to  $D_{het-impact,c/m}$  for *kharif* and *rabi* crops, respectively. We expect  $\alpha_7 < 0$  for both these impacts.

To estimate the differential impacts on mandis with low bank penetration vis-a-vis high bank penetration we set  $D_{het-impact,c/m}$  to one for mandis in districts with low bank penetration, and zero otherwise. Bank penetration is measured at the district level based on percentage of villages within a district with at least one commercial bank within 5 kms. of the village and come from the Census of India, 2011. We divide the sample into terciles, based on the percentage of villages with access, where the first tercile indicates low penetration (lower percentage of villages with access to banks) and the third tercile indicates high penetration. We assign the dummy variable,  $D_{het-impact,c/m}$  as one for mandis falling into the first tercile, and zero for *mandis* in the second or third terciles. The dummy variable,  $D_{het-impact,c/m}$  in Model 2 is defined similarly to examine the differential impacts in mandis which are in districts with low ATM density, relative to the ones with high ATM density. For both bank penetration and ATM density, we expect  $\alpha_7 < 0.30$ 

We also examine variation in impacts across mandis in districts with high market density versus those in districts with low market density. Market density is captured as the number of mandis within a district. We define  $D_{het-impact,c/m} = 1$  for mandis in the first tercile (low market density) and zero otherwise. We expect that mandis within districts with high market density provided farmers more number of options to sell their produce following the cash crunch, and hence the impacts are lower than in mandis with low market density, so that  $\alpha_7 < 0$ .

Further, we also estimate Model 2 to assess the variation in impacts by organizing mandis according to share in total value of trade in the comparison years. Mandis with less than 2% share in trade value take the value 1, as opposed to the rest. Trade diversion could involve both a migration to bigger mandis where the prospect for finding a buyer is higher or away from these if they are far relative to smaller mandis. Finally, we assess the impacts on mandis in districts which are identified as urban centres (district with cities with more than one million inhabitatnts) vis-a-vis other districts. Mandis in these districts are assigned the dummy variable,  $D_{het-impact,c/m}$  value of one, and zero otherwise. A contraction of consumer demand and the difficulty of getting produce to the big urban centres is likely to translate into a higher negative impact near urban centres. At the same time, better access to cash might support demand and mute the negative impacts. For both these models  $\alpha_7$  could be either greater or less than 0.

### 4 Results

#### 4.1 Impact on trade value

Our main results are the DD estimates from Model 1. The dependent variable is the logarithm of value of arrivals for each *mandi*, by commodity, each day. We run 233 regressions to estimate the impact of demonetization on the value of trade for incrementally longer windows following the date of demonetization up until the whole period spanning 233 days (from November 8, 2016 to June 30, 2017). This regression pools all commodities traded in each *mandi* and to account for commodity specific variation, in addition to the controls detailed in Model 1, we use commodity fixed effects. Figure 7 shows the average treatment effects with successively larger windows for regressions with and without commodity fixed effects. The largest impacts occurred within a fortnight of demonetization with a trade displacement effect of around 13% on average at its worst. Thereafter, we observe a steady revival of markets that plateaus quickly after a few days, suggesting reluctant recovery. Remarkably, it seems that the recovery stalled altogether after the 200 day mark. By the end of 233 days

 $<sup>^{30}</sup>$ Chodorow-Reich et al. (2018) argue that the distribution of new notes across different regions in India was almost random, at least in the first few months of demonetization. Since banks and ATMs were the only mode of new currency notes dissemination to public, the extent of shock would have been further exacerbated in regions with low bank / ATM density.

![](_page_18_Figure_0.jpeg)

![](_page_18_Figure_1.jpeg)

*Notes:* The graph plots the point estimates along with 95% confidence intervals of the treatment effects obtained from estimating the DD regression from Model 1. The model is estimate with commodity effects and without commodity effects. The confidence intervals are based on robust standard errors.

after demonetization, mandis were still seeing an average loss of value of trade to the extent of 10% per mandi per day.

We find that all of these results are statistically significant at 1%. This shows that the impact of demonetization persisted even after eight months. This is in sharp contrast to the government's narrative that agriculture showed significant resilience to the effect of demonetization (Chand and Singh, 2017). The apparent displacement of domestic agricultural trade in value terms could come from a decline in arrivals (supply-side) or a collapse in prices (demand-side) or from a combination of both and we examine this question in detail later.

Despite controls for time-varying trends across the demonetization and comparison years and for the pre-November 8 dip in 2016 due to Diwali, there could still be systematic unobservable factors that confound our identification of the causal impact of demonetization. We therefore implement two sets of of placebo tests - 'in-year' placebo and 'in-time' placebo. The 'in-year' placebo assumes that demonstration happened on November 8 in another year, and not in 2016. This involves dropping 2016-17 from the dataset and setting each year from 2011-12 to 2015-16 as the year of demonstration, and computing the impacts using the remaining control years. The 'in-time' placebo assumes that the year of demonstration was the true year, 2016-17, but occurred on a date before the actual date, that is, November 8, 2016. We start by advancing the date of demonstration by one day at a time, and continue to use the remaining years as control. However, we truncate the dataset at November 8 to assess the placebo effect. We start by setting the faux date of demonstration as November 7, and compute the 1-day impact on minimum value of trade, then set it as November 6 to compute the 2-day impact, and so on, until November 1, for which we compute the 5-day impact of presumed demonetization. We implement the 'in-time' placebo for the faux years too. The effect estimated from both these placebos should either show no patterns or have patterns that are different from that implied by demonstration. In particular, for 2016-17 if the impacts we see are indeed due to demonstration, we should see a significant difference

![](_page_19_Figure_0.jpeg)

![](_page_19_Figure_1.jpeg)

*Notes:* The graph presents the coefficient estimates based on 'in-year' and 'in-time' placebos. For comparison, the plot also shows the treatment effects (in black line) obtained from the DD estimation of Model 1.

in the 'in-time' placebo pre and post demonstration, but such a different should be absent for the faux years.

We present the results of both sets of placebos in Figure 8. The gray lines from day 1 to 233 represent the DD estimate for 'in-year' placebos. We superimpose the DD estimated impact for year 2016-17 with a black line. The figure makes it apparent that the estimated DD effect of 'in-year' placebos is unusually large relative to the impacts observed for placebo years. The figure also shows the 'in-time' placebos for five days preceding demonetization. These are the estimates before the dashed vertical line, which represents the first day after demonetization. The estimates turn out to be very noisy with no clear pattern for these placebo days. For 2016-17 the 'in-time' placebos are statistically not different from 0 at the 5% level. These provide confidence that the estimated significant impacts from 2016-17 DD are indeed attributable to demonetization.<sup>31</sup> Our results hold with alternate models - using trade at maximum value, with variety fixed effects, standard errors clustered by mandi-crop.<sup>32</sup>

### 4.2 Heterogeneity of impacts

Estimates from the DD models represent the average impacts across *mandis*. How do these impacts vary across commodity categories (such as perishable and non perishables, *kharif* 

 $<sup>^{31}</sup>$ We implemented a placebo for the crop year 2014 as well (not shown in Figure 8) where consistently the year shows a positive 'impact' of 10%. Given the extraordinarily high trade post-Nov 8 for 2014 relative to other years, we reestimate our main DD model dropping crop year 2014 from our comparison group. We find that the effects do not change. These results are available with the authors.

 $<sup>^{32}</sup>$ We also estimated the model without commodity effects and one with variety effects fixed effects and one using aggregates (over commodities) value of trade per *mandi* per day. These results are available with the authors and a majority of them show stronger negative impacts of demonstration, so that the impacts we present can be seen as a somewhat conservative estimate.

and rabi crops) and across mandis (based on their locations, access to banks)?

The DDD estimates are mostly along expected lines (Equation 2). Columns 3-6 in Table 3 show the  $\alpha_7$  estimates for differences across commodity categories. In the weeks immediately after demonetization, perishables saw a decline in total value of trade in the range of 10-17% more in Week 3-7 (22-50 days). Even after 33 weeks (233 days), we see that the decline in total value of trade for perishables was 6.4% more than non perishables. *Kharif* crops, whose harvests were trading at peak volumes does not show a negative impact of the event in the short term. We in fact see a positive  $\alpha_7$ . The effect may be driven by the commodities such as paddy which saw heavy volumes of government procurement in the period following demonetization. However, over time, we begin to see strong negative impacts *Kharif* crops, which at the end of 33 weeks was 4% more than for *rabi* crops.

Mandis located in districts with lower market density experienced a larger loss in value of domestic trade (6%) relative to those in districts with more regulated markets (Column 7, Table 3). The size of the mandis captured by market share however does not seem to have mattered. For a brief period, smaller mandis seem to have crowded in trade at the expense of larger mandis. Presumably during that time, the advantages of better prospects of finding a buyer in the larger mandis were trumped by the higher transactions costs associated with moving produce all the way to the bigger mandis. It appears that mandis in districts with cities with more than one million inhabitants fared worse than those in less urban districts. The former mandis lost 2.4% more trade than the latter. This is consistent both with a collapse in demand in major consumption centres or inability of traders to move the produce to consumption centres. Both explanations are plausible and the latter interpretation in particular is largely consistent with our findings on bigger mandis described previously.

*Mandis* in districts that had better access to commercial banks had smaller adverse impacts relative to other *mandis*. Mandis with higher bank penetration saw a lower decline in total value of trade relative to the ones with low bank penetration (1-6.1%). Over eight months after demonetization, these differences disappear, as one would expect. Access to ATMs on the other hand had no impact, likely many ATMs routinely ran out of cash or not get timely replenishments. ATMs also had to be recalibrated to dispense new notes and this was a long drawn out process. This result is therefore not surprising.

### 4.3 Sources of impacts: Arrivals versus Prices

Our findings thus far are broadly consistent with expected outcomes and have an intuitive interpretation. Yet it is unclear what is driving these impacts. Is the decline in value of trade led predominantly by the supply-side factors or demand-side factors or both? In this section, we attempt to parse the impacts on value to see if they are generated by declines in arrivals and/or prices. In the absence of clear ways to separate these two impacts, we interpret the price effect as representing demand-side effects, since *mandi* prices are typically set by traders and reflects their demand for farm produce. This is especially the case since our models to estimate price impacts also control for quantity of arrivals. Arrivals are based overwhelmingly on farmers' decision to take the produce to *mandi*. Only a fraction of the farmers hold their

stock for sale.<sup>33</sup> We can therefore interpret the decline in arrivals as approximating supplyside effects. To uncover these patterns, we analyze each of the 35 commodities separately, in part, because aggregating different units and prices are problematic but also to be able to identify systematic differences between crop characteristics or groups, discussed later in this section.

We estimate the following models for arrivals and prices respectively.

$$\ln Y_{c,m,t} = \beta_0 + \beta_1 D_{post-Nov8,t} + \beta_2 D_{2016,t} + \beta_3 D_{post-Nov8,t} \times D_{2016,t} + \zeta X_{c,m,t} + \epsilon_{c,m,t}$$
(3)

where  $Y_{c,m,t}$  denotes the logarithmic values daily arrivals in tons for commodity, c, mandi m, and date, t. Similarly, to analyze the impact on prices  $(\ln P_c, m, t)$ , we estimate the following regression:

$$\ln P_{c,m,t} = \gamma_0 + \gamma_1 D_{post-Nov8,t} + \gamma_2 D_{2016,t} + \gamma_3 D_{post-Nov8,t} + \gamma_4 Y_{c,m,t} + \zeta X_{c,m,t} + \eta_{c,m,t}$$
(4)

We include logarithmic values of arrivals  $(Y_{c,m,t})$  in the specification for prices (Model 4) to account for the influence of supply on prices. Thus the coefficient,  $\gamma_3$  provides an estimate of the overall impact on prices.  $\beta_3$  and  $\gamma_3$  represent the coefficient of interest, which capture the average impact of demonetization on arrivals, and prices in percentage terms. We use the same set of controls as we did for the previous models. As with the main regression, we estimate the regression for arrivals and prices using varying window sizes ranging from 1 days to 233 days after demonetization (Section 3.2).

We present results eight commodities as illustrative examples of the heterogeneity in impacts - these *kharif* crops, representing, different commodity groups, include paddy, soyabean, cotton, tur (pigeon pea), tomato and potato. Paddy markets involve heavy government intervention through procurement for food distribution. Soyabean, an oilseed of considerable importance is non-perishable and has strong industry linkages. Cotton is a high value cash crop that can be stored. Tur is a key pulse in many Indian diets. Tomato and Potato represent two of the most important horticultural crops in the country, of which tomatoes are highly perishable. A and Tables 7-13 present the results for all commodities.

#### 4.3.1 Impact on arrivals

Figure 9 shows the  $\beta_3$  estimates along with the 95% confidence intervals based on Model 3 from the regression on arrivals for these commodities.

The  $\beta_3$  coefficient for paddy indicates that there was, in fact, a positive impact on arrivals after demonetization, implying higher arrivals. High procurement by various state agencies<sup>34</sup>

<sup>&</sup>lt;sup>33</sup>A nationally representative survey of farmers conducted in 2012-13 suggests that for most crops, Indian farmers tend to sell their entire harvest in one lot and usually to one buyer.

<sup>&</sup>lt;sup>34</sup>As much as 30% of annual production of rice is procured by the Government and much of this is procured during November to February. While some of it is procured in the form of rice from millers, a significant share is bought as paddy and custom milled by the government. Payment for these procurements is, in most cases, made directly to the bank account of the farmer, with the exception of two states, where it is first transferred to the bank accounts of commission agents, who then transfer it to farmers' bank accounts.

![](_page_22_Figure_0.jpeg)

Figure 9 Estimated effect of demonetization on arrivals

Notes: The graphs show the  $\beta_3$  coefficient estimate and 95% confidence intervals based on the regression specified in Equation 3. The x-axis shows the size of the event window. Confidence intervals are based on robust standard errors.

justify this result. Government reports suggest that paddy procurement for the season 2016-17 as of February 28, 2017 was 8.27% higher than the previous year (Government of India, 2016a). *Mandis* could therefore have crowded in paddy trade.

In the case of soyabean, initially, there was a severe impact of demonetization, with arrivals falling by as much as 80% by Day 7. The situation improved after a few days, with the decline in arrivals reducing to 50%, but continue to be significantly low. Even after 233 days, there are no signs of recovery. Like, soyabean, cotton arrivals too declined by 25% immediately after demonetization, with no sign of recovery. Given the non-perishable nature of the two commodities, the finding is attributable to the supply-side impact.

Among pulses, we see some impact on tur arrivals in the initial few days of demonetization, but it recovered in later weeks.

For the two horticultural commodities, tomato and potato, as expected, we do not see a decline in arrivals of these commodities. The effects are not statistically different from zero. Tomato is highly perishable and for potato, other than in eastern India, access to cold storages is still somewhat limited, restricting the ability of farmers to store the crop. Thus, as expected, the results indicate that the supply-side factors were absent in perishable commodities.

#### 4.3.2 Impact on prices

Commodity-wise price impacts are estimated based on specific regressions described in Model 4. Figure 10 presents  $\gamma_3$  estimates and the corresponding 95% confidence intervals for the same set of commodities presented in Section 4.3.1.

For both paddy and soyabean, there was no impact on prices after demonetization. Cotton prices increased in the range of 2-5% after demonetization. In the case of soyabean and cotton, the steep decline in arrivals caused prices to increase, given relatively stable demand from solvent extractors and ginning units and spinning mills. Further, as discussed in Section 4.3.1, paddy and cotton are also procured by the state, hence the payments for these commodities is made via checks. In addition, higher purchase of paddy by those seeking to dispose old illegal currency, as a way of utilizing the hoarded black money, could have kept the demand high, and buoyed prices. <sup>35</sup> Prices of tur on the other hand show a decline after a week of demonetization, in the range of 2-4%. A possible reason for the observed fall in both prices and arrivals of tur could be attributed to the bumper crop that was observed in 2016-17, that might have led farmers to continue selling even at lower prices on account of storage constraints <sup>36</sup>

Tomato saw a significant decline in prices in the range of 2-7%, but the impacts reduced after 120 days. In contrast, we see a larger decline in the case of potato prices, with little signs of recovery. Prices of potato show a decline of 9-13% in the first few weeks after demonetization, and the effect continues to remain even after 233 days. The larger decline in both tomato and potato prices is in line with the hypothesis that relatively more perishable commodities where farmers did not have a choice to store were sold at significantly low prices

<sup>&</sup>lt;sup>35</sup>See Demonetisation effect: cotton arrivals wilt, but prices bloom, Hindu Business Line, November 7, 2016.

<sup>&</sup>lt;sup>36</sup>See As prices head south, tur dal farmers seek centre's support, Business Line, Decemeber 6, 2016 and Commodity profiles for Pulses, March 2017

![](_page_24_Figure_0.jpeg)

Figure 10 Estimated effect of demonetization on prices

*Notes*: The graphs show the  $\gamma_3$  coefficient estimate and 95% confidence intervals based on the regression specified in Equation 4. The x-axis shows the size of the event window. Confidence intervals are based on robust standard errors.

following demonetization. At the same time, this is also consistent with demand contraction, either at the consumer or traders' end.

In summary, the results indicate the greater dominance of supply-side factors for nonperishable commodities (e.g. soyabean and cotton). Commodities such as paddy which are procured by state agencies, in fact, instead saw a positive supply-side impact of demonetization due to higher purchases by these agencies. Perishable commodities such as tomato and potato saw

### 5 Robustness checks and caveats

In this section, we validate our findings in several ways. We first focus on commodities that were not impacted by demonetization as falsification tests. If the withdrawal of notes only impinges on cash transactions, we would not expect it to impact those commodities that already have been contracted or where trade is based on electronic payments. International trade too would not get affected since most trade occurs based on prior, forward contracts. Further, to the extent that such trade is in processed forms of agricultural commodities, the export of processed commodities would remain unaffected as the processing would have likely happened pre-demonetization. For exportables, non-delivery on contracts to international clients often has serious costs in terms of reputation. For these reasons too, we believe that exporters would have found ways of tiding over the crisis and one would not expect negative impacts of demonetization. To assess if this is indeed the case, we focus on two sets of export commodities: five varieties of coffee (robusta, arabica, plantation, ground, instant) and five oilmeals (soyabean, rapeseed, groundnut, ricebran, castorseed). A robustness check for each of the five coffee exports and oil meals exports shows no effects, when a similar difference in differences strategy is adopted using monthly export data from 2012-2017. Results from these tests, reported in Table 4 lends credence to our findings on demonetization impacts.

Our earlier results also suggested that commodities where there is government intervention may have been affected to a lesser extent. We focus on milk marketing in the Indian state of Maharashtra, where three types of buyers dominate, the government dairies, private dairies and farmer-owned and managed dairy cooperatives. This allows us to check if procurement by government has a cushioning influence on the potential negative impacts on trade post-demonetization. In the case of milk, we find, as expected, that government procurement of milk shows no impacts (Table 4). However, procurement by private players and cooperatives are impacted suggesting that the latter likely faced cash shortages in the wake of demonetization. Similarly, the results on procurement of grain are consistent with the patterns found in the *mandi* data. Paddy procurement before milling is higher postdemonetization relative to other years and to before demonetization, but this is not the case with other grains. These estimations use monthly data and do not control for rainfall and are hence best interpreted as a coarse consistency check.

We also analyze data on the quantity and value traded on the futures market platform, the National Commodities and Derivatives Exchange (NCDEX) to see if the patterns of impacts on select commodities are consistent with those from *mandi* trades. While overall trade on the NCDEX (both agriculture and non-agricultural commodities) declined (results not shown here), analysis for an illustrative list of commodities comprising wheat (foodgrain), soyabean

(oilseed/pulse), cotton (fibre) and turmeric (spice) that had adequate data is reported in Table 4. We find, as with the results for *mandi*, cotton and wheat show no impacts whereas the impact on turmeric and soyabean is quite substantial with the value traded showing a larger negative impact relative to quantity, suggesting that prices were impacted as well. These patterns correspond broadly to the results for *mandis*.

One concern with attributing impacts from the analysis to demonetization is the contemporaneous election of a new president in the United States. We believe this is not a concern for several reasons. Other than a few commodities that are integrated with global markets, most agricultural commodities in India are somewhat insulated from world trade. There is not much evidence that the US elections impacted agricultural commodity markets worldwide. Given that India is not a key trading partner with the US for most agricultural commodities, this is perhaps an unlikely confounding factor. Existence evidence suggests a 0.9 to 1.5% decline in soy, corn and wheat futures on November 9, 2016, attributed to the election results in the US, but nothing beyond.

While our research suggests that there is an impact on many commodities, this effect may be overestimated if one believes that farmers are diverting trade away from *mandis* to local markets. In this case, the impacts estimated here represent at least in part displacement of trade rather than destruction of trade. In the absence of reliable data it is difficult to get a sense of the extent of displacement.<sup>37</sup> Even with these caveats, it is possible that our estimates of trade displacement potentially seriously underestimates actual welfare losses to farmers. If, as our field based evidence suggest, transactions did occur at specified prices, but there was only an exchange of goods but not of money with traders promising farmers to pay them in four or five months, the time lag between trade and payments entails a significant loss of income. To tide over the cash crunch and transacting virtually fully on credit, many farmers were borrowing from informal lenders at very high interest rates / consumption loans.<sup>38</sup> One would then expect any negative impacts of demonetization to manifest with a lag akin to a "sleeper effect". Similarly, the loss of value traded in domestic regulated market entails a loss in revenue earned by the government in terms of *mandi* fees and taxes and a similar loss to commission agents, brokers and workers in these markets. Our paper does not venture to estimate the potential loss to these stakeholders.

We also stop short of estimating longer term consequences of demonetization beyond seven months since it is difficult to gauge whether we are seeing second round effects of responses to demonetization rather than demonetization itself. For example, if farmers were holding out in order to cope with demonetization, it could well be that delayed arrivals cause potential glut in the markets - as all the stored stocks make their way into the market within a narrow window - thereby bringing down prices. The reverse could also be true, that the price decline post-demonetization attracts traders and processors presumably with better access to credit or financial resources, wish to take advantage of the low prices to buy up stocks, leading to the opposite effect and crowding in trade at the *mandi*. It is virtually impossible to parse these effects through secondary data. In addition, the anticipation of the introduction of Goods and Services Tax (GST) complicates clean identification beyond

 $<sup>^{37}</sup>$ Estimating outside-*mandi* trade based on marketed surplus estimates applied to secondary data on production are notoriously unreliable in the context of Indian agriculture.

<sup>&</sup>lt;sup>38</sup>As one farmer in the southern state of Tamil Nadu put it "today, anyone who has cash (that is legal tended) is a money lender" January 07, 2017 Field visit, Madurai/Trichy.

a certain window.<sup>39</sup> These caveats are relevant while interpreting the results of our analysis.

## 6 Concluding Remarks

Often, the consequences of monetary policy for the agricultural sector (and perhaps other informal) sectors are left unexamined, likely because of the huge challenges in securing the data to make these assessments. This paper set out to evaluate the short term impacts of demonetization on domestic agricultural trade in India, using daily trade data on arrivals in government regulated markets across the country. Using difference in differences techniques using past years data as controls, we found that demonetization displaced over 13% of daily trade on average in the very short run, the effect tapering off only gradually over the next eight months, the period where our study ends. It is apparent however that the value of trade in the *mandis* never really recovered fully and trade was down by 10% on average, even at the end of eight months.

The impacts estimated in this paper offer insights into the the slowdown in GDP growth rates in the three quarters following demonetization. Our findings also provide some understanding of the farmer discontent in recent months across the country. Several Indian states have seen farmer protests - including Madhya Pradesh, Tamil Nadu, Rajasthan, Maharashtra - in the two years following demonetization, including a 'Long March' which saw 50,000 farmers in Maharashtra walk several hundred kilometres to the state capital to make a representation to the Chief Minister.

Early narratives suggested that demonetization had perhaps not had a big impact (Chand and Singh, 2017). The Economic Survey of India 2016-17, for example, concluded with cautious optimism that perhaps the impacts of demonetization on agriculture had been overstated. "Contrary to early fears, as of January 15, 2017 aggregate sowing of the two major *rabi* crops - wheat and pulses (gram)-exceeded last year's planting by 7.1 percent and 10.7 percent." (Government of India, 2016a). Yet it would seem that these impacts estimated in this paper suggest significant welfare consequences for farmers. As of 2016-17, horticulture production at 300 million tonnes outstripped the production of foodgrains (275 million tonnes). If horticulture trade saw impacts of the magnitude estimated in this paper, especially without improvements even after eight months post-demonetization, one would expect this to reflect perhaps with a lag. It is interesting that although *rabi* sowing and production were healthy, in the immediate aftermath of demonetization, there are marked declines in sowing for the *kharif* season 2017-18 as of September 2017. These shortfalls in sowing figures, despite adequate and timely rainfall, is suggestive then, perhaps, of a lagged response to the monetary shock of demonetization (Table 5).

If, as pointed out earlier, farmers rely on borrowings at usurious interest rates, then the negative consequences of trade displacement could be higher than implied by our estimates. There exist ample evidence on poverty traps that suggest that in the absence of markets for credit and insurance, shocks can push people into poverty and entrap them (Azariadis and Stachurski, 2005; Bowles et al., 2006; Carter and Barrett, 2006; Carter et al., 2007; Krishna, 2004). If on the other hand, demonetization engineers a transformation of the financial

 $<sup>^{39}</sup>$ Goods and Services Tax (GST) is an indirect tax introduced countrywide on 1 July 2017 replacing multiple cascading taxes by the federal and state governments.

landscape in a way that farmers are integrated into the formal banking system, this could hold benefits in the long run in ways that may counterbalance these losses. Whether or how much farmers welfare is impacted remains to be seen, but the results from our analysis point to lingering impacts of demonetization on farmers and adverse distributional consequences overall.

## References

- Agarwal, Sumit, Debarti Basu, Pulak Ghosh, Bhuvanesh Pareek, and Jian Zhang, "Demonetization and Digitization," June 2018. Available at SSRN: https://ssrn.com/abstract=3197990.
- Aggarwal, Nidhi, Sargam Jain, and Sudha Narayanan, "The Long road to transformation of agricultural markets in India: Lessons from Karnataka," *Economic and Political Weekly*, 2017, 52(41), 47–55.
- Angrist, Joshua D and Jörn-Steffen Pischke, Mostly Harmless Econometrics: An Empiricist's Companion, Princeton university press, 2008.
- Anzuini, A., M. J. Lombardi, and P. Pagano, "The Impact of Monetary Policy Shocks on Commodity Prices," *International Journal of Central Banking*, September 2013, 9 (3), 125–150.
- Ardeni, Pier Giorgio and John Freebairn, "Chapter 28 The Macroeconomics of Agriculture," in "Agriculture and its External Linkages," Vol. 2 of Handbook of Agricultural Economics, Elsevier, 2002, pp. 1455 – 1485.
- Azariadis, Costas and John Stachurski, "Chapter 5 Poverty Traps," in Philippe Aghion and Steven N. Durlauf, eds., , Vol. 1 of *Handbook of Economic Growth*, Elsevier, 2005, pp. 295 – 384.
- Banerjee, Abhijit, Emily Breza, Arun G Chandrasekhar, and Benjamin Golub, "When Less is More: Experimental Evidence on Information Delivery During India's Demonetization," Working Paper 24679, National Bureau of Economic Research June 2018.
- Barnett, Richard C., David A. Bessler, and Robert L. Thompson, "The Money Supply and Nominal Agricultural Prices," *American Journal of Agricultural Economics*, 1983, 65 (2), 303–307.
- Belongia, Michael T, "Monetary policy and the farm/nonfarm price ratio: a comparison of effects in alternative models," *Federal Reserve Bank of St. Louis Review*, 1991, 73 (July/August 1991).
- Bernanke, Ben, Mark Gertler, and Mark Watson, "Systematic Monetary Policy and the Effects of Oil Price Shocks," *Brookings Papers on Economic Activity*, 1997, 28 (1), 91–157.
- Bertrand, Marianne, Esther Duflo, and Sendhil Mullainathan, "How much should we trust differences-in-differences estimates?," *The Quarterly Journal of Economics*, 2004, 119 (1), 249–275.
- Bhavnani, Rikhil and Mark Copelovitch, "The Political Impact of Monetary shocks: Evidence from India's 2016 Demonetization," 2018. Available at SSRN: https://ssrn. com/abstract=3095228.

- Bowles, Samuel, Steven N Durlauf, and Karla Hoff, *Poverty Traps*, Princeton University Press, 2006.
- Carter, Michael R and Christopher B Barrett, "The Economics of Poverty Traps and Persistent Poverty: An Asset-based Approach," *The Journal of Development Studies*, 2006, 42 (2), 178–199.
- \_, Peter D Little, Tewodaj Mogues, and Workneh Negatu, "Poverty traps and natural disasters in Ethiopia and Honduras," World Development, 2007, 35 (5), 835–856.
- Chambers, Robert G., "Agricultural and Financial Market Interdependence in the Short Run," American Journal of Agricultural Economics, 1984, 66 (1), 12–24.
- Chambers, Robert G and Richard E Just, "An Investigation of the Effect of Monetary Factors on Agriculture," Journal of Monetary Economics, 1982, 9 (2), 235–247.
- Chand, Ramesh and Jaspal Singh, NITI Aayog, Government of India, Blog series, 2017.
- Chodorow-Reich, Gabriel, Gita Gopinath, Prachi Mishra, and Abhinav Narayanan, "Cash and the Economy: Evidence from India's Demonetization," Working Paper 25370, National Bureau of Economic Research December 2018.
- Ciriacy-Wantrup, Siegfried V, "The Relation of War Economics to Agriculture with Particular Reference to the Effects of Income and Price Inflation and Deflation," *The American Economic Review*, 1940, 30 (1), 366–382.
- **Dewan, Ritu and Radha Sehgal**, *Demonetisation: From Deprivation to Destitution*, Himalaya Publishing House, Delhi, 2019.
- Dharmapala, Dhammika and Vikramaditya Khanna, "Stock Market Reactions to India's 2016 Demonetization: Implications for Tax Evasion, Corruption, and Financial Constraints," Working Paper 844, Coase-Sandor Working Paper Series in Law and Economics 2018.
- Diaz-Bonilla, Eugenio and Sherman Robinson, "Macroeconomics, macrosectoral policies, and agriculture in developing countries," *Handbook of Agricultural Economics*, 2010, 4, 3035–3213.
- Frankel, Jeffrey A., "Expectations and Commodity Price Dynamics: The Overshooting Model," American Journal of Agricultural Economics, 1986, 68 (2), 344–348.
- \_\_, "The Effect of Monetary Policy on Real Commodity Prices," in "Asset Prices and Monetary Policy," University of Chicago Press, 2008, pp. 291–333.
- and Andrew Rose, "Determinants of Agricultural and Mineral Commodity Prices," in Renee Fry, Callum Jones, and Christopher Kent, eds., Inflation in an Era of Relative Price Shocks, RBA Annual Conference Volume, Reserve Bank of Australia, December 2010.
- Ghosh, Jayati, CP Chandrasekhar, and Prabhat Patnaik, Demonetisation Decoded: A Critique of India's Currency Experiment, Taylor & Francis, 2017.

- **Government of India**, "Price Policy for Kharif Crops, Agricultural Marketing Year 2017-18," 2016.
- $\_$ , "State of Agriculture in India 2015-16," 2016.
- Goyal, Aparajita, "Information, Direct Access to Farmers, and Rural Market Performance in Central India," *American Economic Journal: Applied Economics*, 2010, 2 (3), 22–45.
- Hamilton, James D., "Monetary factors in the Great Depression," Journal of Monetary Economics, 1987, 19 (2), 145 169.
- Karmakar, Bikram, Bhuvanesh Pareek, Dylan S. Small, and Pulak Ghosh, "The Effect of Demonetization on Digital Payments in India:Causal Inference in the Absence of Controls," Working Paper November 2018.
- Krishna, Anirudh, "Escaping poverty and becoming poor: who gains, who loses, and why?," World Development, 2004, 32 (1), 121–136.
- Krishnan, Deepa and Stephan Siegel, "Effects of demonetization: Evidence from 28 slum neighbourhoods in Mumbai," *Economic and Political Weekly*, 2017, 52(3).
- Miskimin, Harry A., "Monetary Movements and Market Structure: Forces for Contraction in Fourteenth- and Fifteenth-Century England," *The Journal of Economic History*, 1964, 24 (4), 470–490.
- Reddy, C. Rammanohar, *Demonetisation and the Black Economy*, Orient Blackswan, Delhi, 2017.
- Schuh, G Edward, "The Exchange Rate and US Agriculture," American Journal of Agricultural Economics, 1974, 56 (1), 1–13.

### Table 1 Commodities selected for analysis

The table presents the list of commodities selected for the analysis. Arrivals during *kharif* is computed as percentage of arrivals during October to January in a crop year. Average across 2012-2016 is reported. *Mandis* reported is computed as number of unique *mandis* that reported arrivals in a crop year.

Commodity	Group	Area under cultivation (2015-16, in million hectares)	# of mandis reporting trac	Season le	Arrivals during <i>kharif</i> (%)	
Bajra	Cereals	6.98	437	kharif	50.28	
Jowar	Cereals	5.65	434		37.88	
Maize	Cereals	8.69	762	kharif	56.24	
Paddy	Cereals	43.39	1,073	kharif	76.75	
Ragi	Cereals	NA	104	kharif	35.49	
Rice	Cereals	NA	497		35.58	
Wheat	Cereals	30.23	1,136	rabi	9.46	
Bengal Gram	Pulses	8.35	519	rabi	17.75	
Tur	Pulses	3.75	492	kharif	34.66	
Soyabean	Oilseeds	11.67	450	kharif	63.03	
Mustard	Oilseeds	5.76	582	rabi	16.54	
Groundnut	Oilseeds	4.56	364	kharif	56.62	
Cumin	Spices	0.70	82	rabi	14.25	
Coriander Seed	Spices	0.62	136		17.81	
Dry Chillies	Spices	0.79	79		24.47	
Turmeric	Spices	0.19	100		19.37	
Arecanut	Plantation	0.47	93		40.58	
Cashewnuts	Plantation	1.04	52		6.95	
Copra	Plantation	2.09	66		41.22	
Cotton	Fibre	11.87	464	kharif	64.16	
Brinjal	Vegetable	0.66	646		34.50	
Cabbage	Vegetable	0.39	526		40.51	
Cauliflower	Vegetable	0.43	543		46.05	
Okra	Vegetable	0.49	539		20.64	
Onion	Vegetable	1.23	836		34.05	
Potato	Vegetable	2.13	835		34.52	
Tomato	Vegetable	0.76	724		33.10	
Apple	Fruits	0.31	332		47.50	
Banana	Fruits	0.85	444		34.25	
Guava	Fruits	0.25	186		49.16	
Lemon	Fruits	0.26	241		24.31	
Lime	Fruits	included above	68		29.98	
Sweet Lime	Fruits	0.22	193		23.23	
Orange, others	Fruits	0.46	212		73.25	

 $^{1}$  Area from Agricultural Statistics at a Glance 2016. Some are advance estimates.

 $^{2}$  NA is Not available

### Table 2 How was production in 2016-17 compared to 2003-04 to 2015-16?

This table provides a comparative perspective of production in 2016 in relation to the years 2003-04 to 2015-16. We compare the 2016 production with the minimum, maximum and mean of these years and deem 2016 to have been better if production exceeded the maximum for that period.

Crop	Season	Units	2016 production	Minimum	Maximum	Mean	Was 2016 better?
Rice	Kharif	m.tons	93.88	72.23	92.78	84.1	Better
Wheat	Rabi	m.tons		68.64	95.85	82.9	
Jowar	Kharif	m.tons	2.42	1.71	4.84	3.3	
Bajra	Kharif	m.tons	8.55	6.51	12.11	9.0	
Maize	Kharif	m.tons	19.3	11.48	17.14	14.5	Better
Ragi/Finger millet	Kharif	m.tons	1.85	1.44	2.43	2.0	
Small Millets	Kharif	m.tons	0.34	0.37	0.56	0.5	
Coarse Cereals	Kharif	m.tons	32.45	23.83	33.08	29.2	
Tur	Kharif	m.tons	4.29	2.27	3.17	2.7	Better
Urad	Kharif	m.tons	2.01	0.81	1.43	1.1	Better
Moong	Kharif	m.tons	1.35	0.44	1.53	1.0	
Other Kharif	Kharif	m.tons	1.06	0.49	1.33	0.8	
Groundnut	Kharif	h.t.tons	64.98	31.87	80.58	56.0	
Castorseed	Kharif	h.t.tons	17.31	7.62	22.95	13.4	
Sesamum	Kharif	h.t.tons	6.75	5.88	8.93	7.3	
Nigerseed	Kharif	h.t.tons	1.01	0.76	1.21	1.0	
Rapeseed-Mustard	Rabi	h.t.tons		58.34	81.79	71.5	
Linseed	Rabi	h.t.tons		1.32	1.97	1.6	
Sunflower	Kharif	h.t.tons	1.34	0.68	4.63	2.7	
Soyabean	Kharif	h.t.tons	142.23	68.76	146.66	102.4	
Cotton	Total	lakh bales#	321.23	137.29	359.02	266.7	
Jute	Total	lakh bales	99.05	93.99	112.3	102.9	
Mesta	Total	lakh bales	5.01	5.08	9.9	7.3	
Sugarcane	Total	h.t.tons	3052.46	2338.62	3623.33	3188.0	
Cereals	Kharif	m.tons	126.33	98.59	125.22	113.2769	Better
Total Pulses	Kharif	m.tons	8.7	4.2	7.12	5.552308	Better
Total Foodgrains	Kharif	m.tons	135.03	103.31	131.27	118.8277	Better
Total Nine Oilseeds	Kharif	h.t.tons	233.63	140.12	226.12	182.8054	Better
Jute -Mesta	Total	lakh bales	104.05	102.72	118.17	110.14	
Sugarcane	Total	h.t.tons	3052.46	2338.62	3623.33	3188.014	
Cotton	Total	lakh bales#	321.23	137.29	359.02	266.7269	

<sup>1</sup> Area from Agricultural Statistics at a Glance 2016. Some are advance estimates.

 $^{2}$  # means bales are 170kg. Otherwise bales are 180 kgs.

 $^{3}$  m tons and h.t.tons are million and hundred thousand tons repectively.

bacts across commodities and mandi categories on value of trade after demonetization	us impacts on the value of trade for different commodity and mandi categories from Week 0 to Week 33 after	s are based on the triple difference regression estimation of minimum value of transactions in each mandi each day.	ber of weeks after demonetization. The remaining columns show the results across different subgroups.
Table 3 Heterogeneous impacts across commo	The table presents heterogeneous impacts on the val	demonetization. The coefficients are based on the trip	The first column shows the number of weeks after dem

Days	Week	$\operatorname{Perish}$	ables	$\mathrm{Kh}_{\mathrm{E}}$	urif	Mar	·ket	Mar	ket	Url C	oan	Ba	hk	ΤΑ	N.
	,		ţ		Ę	aen	SILY	SUS	ure en	cen	cres 25	Drat	cnes	peneu	ration
		$\alpha_7$	SE	$\alpha_7$	SE	$\alpha_7$	SE	$\alpha_7$	SE	$\alpha_7$	SE	$\alpha_7$	SE	$\alpha_7$	SE
	0	-0.005	(0.03)	0.135	(0.07)	-0.002	(0.05)	0.006	(0.23)	-0.029	(0.05)	-0.065	(0.04)	-0.009	(0.04)
	1	-0.003	(0.02)	0.200	(0.04)	-0.002	(0.02)	0.011	(0.13)	-0.008	(0.03)	-0.060	(0.02)	-0.042	(0.02)
5	2	-0.052	(0.01)	0.164	(0.03)	-0.026	(0.02)	0.021	(0.10)	-0.033	(0.02)	-0.028	(0.01)	-0.017	(0.02)
5	3	-0.098	(0.01)	0.118	(0.02)	-0.060	(0.02)	-0.030	(0.08)	-0.041	(0.02)	-0.031	(0.01)	-0.010	(0.01)
6	4	-0.140	(0.01)	0.091	(0.02)	-0.085	(0.01)	-0.034	(0.02)	-0.032	(0.02)	-0.019	(0.01)	0.008	(0.01)
0	5	-0.155	(0.01)	0.072	(0.02)	-0.093	(0.01)	-0.022	(0.07)	-0.032	(0.01)	-0.015	(0.01)	0.019	(0.01)
co co	9	-0.171	(0.01)	0.063	(0.02)	-0.105	(0.01)	-0.007	(0.06)	-0.027	(0.01)	-0.012	(0.01)	0.026	(0.01)
0	7	-0.168	(0.01)	0.066	(0.02)	-0.114	(0.01)	0.005	(0.06)	-0.022	(0.01)	-0.017	(0.01)	0.023	(0.01)
2	8	-0.168	(0.01)	0.063	(0.02)	-0.122	(0.01)	-0.010	(0.06)	-0.020	(0.01)	-0.030	(0.01)	0.016	(0.01)
4	6	-0.166	(0.01)	0.080	(0.01)	-0.127	(0.01)	-0.011	(0.06)	-0.022	(0.01)	-0.040	(0.01)	0.013	(0.01)
_	10	-0.166	(0.01)	0.088	(0.01)	-0.132	(0.01)	0.003	(0.05)	-0.025	(0.01)	-0.046	(0.01)	0.009	(0.01)
x	11	-0.156	(0.01)	0.093	(0.01)	-0.135	(0.01)	0.016	(0.05)	-0.031	(0.01)	-0.054	(0.01)	0.008	(0.01)
10	12	-0.148	(0.01)	0.086	(0.01)	-0.134	(0.01)	0.025	(0.05)	-0.029	(0.01)	-0.057	(0.01)	0.008	(0.01)
~1	13	-0.143	(0.01)	0.074	(0.01)	-0.132	(0.01)	0.031	(0.05)	-0.026	(0.01)	-0.061	(0.01)	0.006	(0.01)
6	14	-0.139	(0.01)	0.063	(0.01)	-0.128	(0.01)	0.039	(0.05)	-0.025	(0.01)	-0.062	(0.01)	0.004	(0.01)
J6	15	-0.133	(0.01)	0.039	(0.01)	-0.127	(0.01)	0.052	(0.05)	-0.028	(0.01)	-0.062	(0.01)	0.005	(0.01)
13	16	-0.127	(0.01)	0.021	(0.01)	-0.126	(0.01)	0.053	(0.05)	-0.029	(0.01)	-0.058	(0.01)	0.007	(0.01)
20	17	-0.123	(0.01)	-0.012	(0.01)	-0.122	(0.01)	0.060	(0.05)	-0.030	(0.01)	-0.053	(0.01)	0.009	(0.01)
27	18	-0.116	(0.01)	-0.022	(0.01)	-0.118	(0.01)	0.073	(0.05)	-0.029	(0.01)	-0.048	(0.01)	0.011	(0.01)
34	19	-0.112	(0.01)	-0.049	(0.01)	-0.116	(0.01)	0.076	(0.05)	-0.030	(0.01)	-0.043	(0.01)	0.014	(0.01)
41	20	-0.108	(0.01)	-0.068	(0.01)	-0.112	(0.01)	0.081	(0.05)	-0.033	(0.01)	-0.041	(0.01)	0.013	(0.01)
48	21	-0.103	(0.01)	-0.078	(0.01)	-0.110	(0.01)	0.087	(0.05)	-0.036	(0.01)	-0.041	(0.01)	0.010	(0.01)
55	22	-0.104	(0.01)	-0.099	(0.01)	-0.106	(0.01)	0.086	(0.04)	-0.039	(0.01)	-0.040	(0.01)	0.009	(0.01)
52	23	-0.107	(0.01)	-0.121	(0.01)	-0.100	(0.01)	0.085	(0.04)	-0.035	(0.01)	-0.037	(0.01)	0.008	(0.01)
<u> 6</u>	24	-0.104	(0.01)	-0.116	(0.01)	-0.090	(0.01)	0.082	(0.04)	-0.032	(0.01)	-0.030	(0.01)	0.013	(0.01)
92	25	-0.100	(0.01)	-0.104	(0.01)	-0.083	(0.01)	0.072	(0.04)	-0.031	(0.01)	-0.024	(0.01)	0.017	(0.01)
83	26	-0.092	(0.01)	-0.089	(0.01)	-0.075	(0.01)	0.064	(0.04)	-0.028	(0.01)	-0.020	(0.01)	0.017	(0.01)
90	27	-0.087	(0.01)	-0.081	(0.01)	-0.071	(0.01)	0.057	(0.04)	-0.028	(0.01)	-0.018	(0.01)	0.018	(0.01)
57	28	-0.082	(0.01)	-0.074	(0.01)	-0.069	(0.01)	0.056	(0.04)	-0.027	(0.01)	-0.015	(0.01)	0.018	(0.01)
)4	29	-0.078	(0.01)	-0.067	(0.01)	-0.067	(0.01)	0.056	(0.04)	-0.025	(0.01)	-0.013	(0.01)	0.020	(0.01)
11	30	-0.074	(0.01)	-0.058	(0.01)	-0.065	(0.01)	0.055	(0.04)	-0.025	(0.01)	-0.010	(0.01)	0.022	(0.01)
18	31	-0.071	(0.01)	-0.050	(0.01)	-0.063	(0.01)	0.052	(0.04)	-0.026	(0.01)	-0.007	(0.01)	0.023	(0.01)
25	32	-0.067	(0.01)	-0.047	(0.01)	-0.061	(0.01)	0.055	(0.04)	-0.025	(0.01)	-0.007	(0.01)	0.024	(0.01)
33	33	-0.064	(0.01)	-0.044	(0.01)	-0.057	(0.01)	0.057	(0.04)	-0.024	(0.01)	-0.007	(0.01)	0.024	(0.01)

 Table 4 Robustness Checks: Estimates for select commodities - export, procurement, commodity exchange based trade

This table presents difference in differences estimates for oilmeal and coffee exports, milk procurement in the state of Maharashtra by government, cooperatives and private dairy players, grain procurement by government. In addition, estimates for the value and quantity traded of specific commodities in the National Commodities and Derivatives Exchange (NCDEX).

	Commodity	D-in-D estimates	Standard Error	Details
1	<b>Total Oilmeal exports</b> Soyameal Rapeseed meal Groundnut meal Castormeal	6726.52 -4956.17 1469.74 -65.91 -15763.46	$\begin{array}{c} (61759.54) \\ (59728.63) \\ (18793.42) \\ (151.14) \\ (24495.68) \end{array}$	Monthly data, 2013-2017 (tonnes)
2	Total Coffee Exports	3330.25	(3342.45)	Monthly data, 2001-2017 (tonnes)
3	Total milk procure- ment (Maharashtra)	-40.85*	(16.81)	Monthly data, 2013-2016
	Government	0.25	(0.91)	(in lakh litres per day)
	Cooperatives	-4.60*	(2.07)	
	Private	-35.51*	(14.88)	
4	Total grain procure- ment	-0.14	(0.07)	Monthly data, 2011-2017
	Rice Procurement	-0.17	(0.11)	in log (procurement in ten thousand tonnes)
	Wheat procurement	-0.14	(0.09)	,
	Total grain procurement	-0.14	(0.07)	
	Unmilled Paddy procure- ment	0.61**	(0.14)	
	Coarse grain procurement	-0.5	(0.29)	
5a	NCDEX Quantity traded			Daily data 2013-17
	Wheat	0.080	(0.38)	log (traded qty. in tonnes)
	Turmeric	-1.504**	(0.34)	
	Soyabean	-1.189*	(0.46)	
	Cotton(Shankar/kapas)	-0.014	(0.05)	
5b	NCDEX Value traded			Daily data 2013-17
	Wheat	0.170	(0.32)	log (value in lakhs)
	Turmeric	-1.548**	(0.36)	- · · · ·
	Soyabean	-1.237**	(0.44)	
	$\operatorname{Cotton}(\operatorname{Shankar}/\operatorname{kapas})$	0.007	(0.08)	

 $^1$  Coefficients and standard errors presented for the interaction of November-June (cropyear) and 2016, the year of demonstization.

 $^2$  \*\* refers to 1% level of significance, \*5% level of significance.

 $^{3}$  For milk procurement, the analysis is restricted to the state of Maharashtra, due to data availability.

<sup>4</sup> The full results are available with the authors.

## Table 5 Kharif and rabi sowing, 2016-17 and 2017-18

	Kharif sow	ing %age change	Rabi sowin	ıg %age change	
	2016-17	(5 yr-avg.)	2017-18	(5 yr-avg.)	
Cereals					
Wheat			6.9	4.5	
Rice	-1.3	-4.8	-11.7	-41.2	
Pulses	-3.5	33.7	11.2	13.5	
Gram			10.7	12.0	
Tur	-18.0	10.2	21.2	12.6	
Urad	21.6	72.9	9.0	13.8	
Moong	-8.0	35.5	3.4	-30.5	
Fieldpea			17.4	18.4	
Kulthi	6.1	-71.0	-10.9	68.0	
Lathyrus			9.6	-17.4	
Other pulses	-2.0	43.9	12.1	160.9	
Coarse cereals	-2.5	-3.5	-5.6	-11.6	
Jowar	-7.4	-22.4	-13.9	-15.8	
Bajra	1.9	-6.5	9.3	-93.5	
Ragi	1.0	-12.1	-33.4	-12.7	
Maize	-4.8	9.3	9.4	5.6	
Small millets	-10.9	-27.8			
Barley			7.5	18.8	
Oilseeds	-8.7	-6.0	6.2	-0.7	
Groundnut	-11.4	0.1	3.4	-27.2	
RapeseedMustard			9.3	11.6	
Safflower			-18.6	-53.9	
Sunflower	-14.6	-40.2	-47.4	-65.5	
Sesamum	-12.6	-9.0	-19.8	-81.1	
Linseed			31.1	23.5	
Other Oilseeds			-36.4	241.2	
Soyabean	-7.7	-4.0			
Niger	6.7	-27.7			
Caster	-2.6	-30.7			
Sugarcane	9.4	-0.2			
Jute and Mesta	-6.5	-15.6			
Cotton	18.7	-0.6			

The table presents the area sown in *kharif* 2017-18 (as on 22.09.2017) and *rabi* 2016-17 (as on 03.02.2017).

<sup>1</sup> All India Crop Situation obtained from the website of the Department of Agriculture Cooperation and farmers welfare, URL: http://agricoop.nic.in/all-india-crop-situation?page=1.
<sup>2</sup> Missing data means the crop is not grown mainly in that season.

# For Online Publication

# A **RBI** Notifications

S.No.	DATE OF THE	CIRCULAR NUMBER	TITLE OF THE CIRCULAR	CONTENT									
	CIRCULAR												
1.	08-11-2016	RBI/2016-2017/122 DCM(plg)No.1226/10 .27.00/ 2016-17	Withdrawal of Legal Tenders Character of existing Rs500/-and Rs 1000/- Bank notes	<ol> <li>Existing bank notes of Rs 500/- and Rs 1000/- (hence referred to as specified bank notes(SBNs)) cease to exist as legal tenders from November 9, 2016.</li> <li>Urban and State cooperative banks are allowed to exchange SBNs of aggregate value of 4000/- or below.</li> <li>Limit of cash withdrawal from bank account over the counter is Rs 10,000/- per day subject to overall limit of Rs 20,000/- a week from date of notification to end of business hours of November 24, 2016, after which limit shall be revised.</li> <li>Withdrawal from ATMs restricted to RS2000/-</li> <li>Business correspondents may be allowed to exchange SBN up to Rs4000/-per person in case of bank branches.</li> </ol>									
2.	09-11-2016	RBI/2016-2017/115 DCM(plg)No.1241/10 .27.00/ 2016-17	Withdrawal of Legal Tenders Character of existing Rs500/-and Rs 1000/- Bank notes	limit of Rs2000/- per day per card and 20,000/- in a week across all the channels is applied to all customers.									
3.	10-11-2016	RBI/2016-2017/123 DCM(plg)No.1251/10 .27.00/ 2016-17	Withdrawal of Legal Tender Character of existing Rs500/- and Rs1000/-Bank notes-Limit of Withdrawal of Cash	Interbank transfers, post offices, money changers in international airports, white label ATM operators are exempt from over the counter limits									
4.	13-11-2016	RBI/2016-2017/129 DCM(plg)No.1272/10 .27.00/ 2016-17	Withdrawal of Legal Tender Character of existing Rs500/- and Rs1000/-Bank notes- Revision in limits	Limit for exchange of SBNs over the counter increased from existing Rs 4000/- to Rs 4,500/- ATM limit increased from Rs 2000/- to Rs2,500/-per day. The weekly limit of withdrawal was increased from Rs20,000/- to Rs24,000/									
5.	14-11-2016	RBI/2016-2017/130 DCM(plg)No.1273/10 .27.00/ 2016-17	Withdrawal of Legal Tender Character of existing Rs500/- and Rs1000/-Applicability of the Scheme to DCCBs	DCCBs can allow their existing customers to withdraw money from their accounts up to Rs 24,000/-per week up to November 24,2016. However no exchange or deposit facility against SBN should be entertained by them.									
6.	14-11-2016	RBI/2016-2017/131 DCM(plg)No.1274/10	Withdrawal of Legal Tender Character of	Persons with current accounts functional for the last three months or more are allowed to									

		.27.00/	Specified Bank Notes-	withdraw up to Rs50,000/- per week.
		2016-17	Expanding the distribution	
			location for deposit and	
			withdrawal of cash	
7.	16-11-2016	RBI/2016-2017/135	Withdrawal of Legal	For deposits more than Rs50,000/- in cash a
		DCM(plg)No.1287/10	Tender Character of	copy of the PAN card has to be submitted in
		.27.00/	Specified Bank Notes-	case the bank account is not seeded with the
		2016-17	Compliance with provision	PAN.
			of 114B of the Income Tax	
	47.44.2046		Rules ,1962	
8.	17-11-2016	RBI/2016-2017/139	Withdrawal of Legal	Limit of exchange of SBNs in cash, across the
		DCIVI(pg)N0.1502/10.	ovisting ReEOO/ and	counter of the ballies shall be RS2000/- per
		27.00/	Ps1000/-Rank notes-	person with effect from November 18, 2010.
		2010-17	Exchange over the	
			counters	
9.	20-11-2016	RBI/2016-2017/141	Withdrawal of Legal	Banks may continue to dispense Rs 50/- and
		DCM(plg)No.1304/10	Tender Character of	Rs 100/- bank notes through the non –
		.27.00	existing Rs500/- and	recalibrated ATMs until they are re-calibrated
			Rs1000/-Bank notes-	with no change in the withdrawal limits.
			Revision in limits	
10.	21-11-2016	RBI/2016-2017/142	Withdrawal of Legal	Holders of current / overdraft / cash credit
		DCM(plg)No.1317/10	Tender Character of	accounts, which are operational for the last
		.27.00/	Specified Bank Notes-	three months or more, may now withdraw up
		2016-17	Cash Withdrawal Limits	to Rs50000 /-in cash, in a week.
11.	21-11-2016	RBI/2016-2017/146	Withdrawal of Legal	Farmers may be allowed to draw up to Rs
		DCM(plg)No.1323/10	Tender Character of	25000/- per week in cash from their loan
		.27.00/	existing RS500/- and	(including Kisan Credit Card limit) or KYC
		2016-17	RS1000/-Bank notes-	compliant deposit accounts.
			Revisions	mandic are allowed to withdraw in cash Bs
				$50.000/_{-}$ in a week from their KVC complaint
				current account subject to certain terms and
				conditions
12.	22-11-2016	RBI/2016-2017/148	Making cash available for	To ensure adequate credit for farmers in the
		DCM(plg)No.1345/10	Rabi Crop Season -	Rabi season, an estimated Rs 35.000/- crore
		.27.00/	Advisory to banks	would be required by the DCCBs for sanctions
		2016-17		and disbursement of crop loan to the farmers
				at the rate Rs10,000/- crore per week.
				NABARD would utilize its own Cash Credit
				limits up to about Rs 23,000/- crore to enable
				DCCBs to disburse the required crop loans to
				PACS and farmers.
13.	23-11-2016	RBI/2016-2017/151	Deposit of Specified	Banks are advised not to accept SBNs for
		DCM(plg)No.1351/10	Banknotes (SBN) in Small	deposits in Small Savings Scheme with
		.27.00/2016-17	Saving Schemes	immediate effect.
14.	24-11-2016	RBI/2016-2017/155	Discontinuation of over	No over the counter exchange (in cash) of

		DCM(plg)No.1391/10	the Counters Exchanges of	SBNs will be permitted after midnight of
		.27.00 /	SBN	November 24, 2016, instead SBNs can be
15	25-11-2016	2010-17 RBI/2016-2017/158	Withdrawal of cash –	Cash withdrawals (including ATM
15.	25 11 2010	DCM(plg)No.1424/10	Weekly limit	withdrawals) allowed up to Rs 24,000/- per
		.27.00/		week, till further instructions.
		2016-17		
16.	28-11-2016	RBI/2016-2017/163	Withdrawal of cash from	Withdrawal of deposits made in current legal
		DCM(plg)No.1437/10	bank deposit accounts -	tender notes on or after November 29, 2016
		.27.00/	Relaxation	beyond the current limits; preferably,
		2016-17		available higher denominations bank notes of
				RS 2000 /-and RS 500/- are to be issued for
17	29-11-2016	RBI/2016-2017/165	Accounts under PMIDY -	Such withurawais.
17.	29-11-2010	DCM(n g)No 1450/10	Precautions	allowed to withdraw Rs10_000/- from their
		.27.00/		account, in a month, while Non KYC compliant
		2016-17		account holders may be allowed to withdraw
				Rs 5,000/- per month from the amount
				deposited through SBNs after November 09,
				2016 within the overall ceiling of Rs10,000/
18.	19-12-2016	RBI/2016-2017/189	Withdrawal of Legal	Restrictions on deposits of SBNs into bank
		DCM(plg)No.1859/10	Tender Character of	accounts 2016 are as indicated below:
		.27.00/	existing RS500/- and Rs1000/-Rank notes(SBN)-	a. Tenders of SBNs in excess of RS5000/- Into
		2010-17	Denosit of Specified Bank	only once in KYC complaint accounts
			Notes into bank accounts	during the remaining period till December
				30, 2016 after due inspection.
				b. Tenders of SBNs up to Rs 5000/- in value
				received across the counter will allowed
				to be credited to bank accounts in the
				normal course until December 30, 2016.
				c. Non KYC compliant credits may be
				d The equivalent value of SPNs tendered
				may be credited to an account maintained
				by the tenderer or a third party account at
				any bank in accordance with standard
				banking procedure and on production of
				valid proof of Identity.
				e. The above restrictions shall not apply to
				tenders of SBNs for the purpose of
				aeposits under the laxation and
				Mantri Garib Kalvan Vojana 2016
19	30-12-2016	RBI/2016-2017/204	Cash Withdrawals from	Cash withdrawal from ATMs has been
1.5.	50 12 2010	DCM(plg)No.2142/10	ATMs –enhancement of	increased with effect from January 01.2017.
		.27.00/	Daily limits	from the existing Rs 2500/- to Rs 4500/- per

		2016-17		day per card .
20.	16-01-2017	RBI/2016-2017/213	Enhancement of	Limit on withdrawal from ATMs has been
		DCM(plg)No.2559/10	withdrawal limits from	enhanced from current limit of Rs4,500/- to
		.27.00/	ATMs and Current	Rs10,000/- per day per card and from
		2016-17	Accounts	RS50,000/- to RS1,00,00,/- per week for
				cuurent, Overdraft and cash credit accounts.
21.	30-01-2017	RBI/2016-2017/217	Limits on Cash	Limits placed on cash withdrawal from Saving
		DCM(plg)No.2905/10	withdrawals from Banks	Bank accounts will continue till February 01,
		.27.00 /	accounts and ATMs -	2017 while limits on Current Accounts/ Cash
		2016-17	Restoration of status quo	Credit Accounts/Overdraft Accounts stand
			ante	withdrawn.
22.	08-02-2016	RBI/2016-2017/224	Removal of limits of	Limit on cash withdrawals from Savings Banks
		DCM(plg)No.3107/10	withdrawal of cash from	Accounts will be enhanced to Rs 50,000/- per
		.27.00/	Savings Bank Accounts	week( from current limit of Rs24,000/- per
		2016-17		week) and no such limit effective March 13,
				2017.
1				1

## B Impacts on prices and arrivals of individual commodities

Table 6 shows the impact on arrivals in the regulated *mandis* after the note ban of Nov 8, 2016. As hypothesized, we find that the arrivals fell in the week after the note ban, across almost all non perishable commodities. The decline in arrivals for perishable commodities is much lower than the non perishable commodities.<sup>40</sup> Some perishables show even a positive change in the first week after demonstration. This is similar to the trends observed in control years. The table also reports change in arrivals two weeks after demonetization relative to the week prior the event. Apple, which has a relatively longer shelf-life than the other perishables analyzed in the study, also saw a significant decline in arrivals in the two weeks post demonetization. While it appears that the decline in a few commodities such as maize, rice, tur, cashewnuts recovered slightly, several other commodities continued to see a sharp fall. To put these numbers in perspective, we also examine the mean week-on-week changes in arrivals for the control years as well. Except for paddy and raw turmeric, we do not see such a sharp decline in non perishables arrivals in the remaining years. The last column in the table also shows the proportion of arrivals that come during the *kharif* season. The table shows that the impact of the event was not only restricted to *kharif* crops such as maize and soyabean but was also observed on *rabi* crops such as wheat and Bengal gram.

We estimate separate regressions for each commodity to analyze the differential impacts on arrivals and prices across commodities. Table 7-10 provide coefficient estimates of the interaction term that captures the treatment effect. We find that the commodities that were hit the hardest in the immediate aftermath of demonetization were soyabean and coriander seed.<sup>41</sup> Soyabean arrivals fell by 75% per *mandi* per day over the seven to fifteen day period following demonetization. Coriander seed, on the other hand, saw a decline in trade to the extent of 98% over the same period. Both these commodities started showing signs of recovery over the course of 30 days following demonetization, however the impacts remain strong even after 200 days. We also see that commodities such as paddy saw a positive impact on trade even in the week immediately after the event of demonetization. This could be attributed to the increase in procurement of paddy by government to reduce the possible impact of the event.<sup>42</sup>

Perishable commodities including apple, okra, brinjal, cauliflower, potato show an impact on arrivals in the range of 3-216% following the first fifteen days of demonetization. Even though the size of the impact is smaller than non perishables, the most likely reason for this variation in impacts is due to demand and supply forces. While in the case of perishables, only the demand may have shrunk, depressing only the prices, in the case of non perishables, it is likely that both demand and supply was shrunk.

We also analyze the impact on prices obtained from regressing prices for each commodity. Table 11-14 presents the treatment effects for each commodity. As expected, non perishables

<sup>&</sup>lt;sup>40</sup>It is likely that perishables saw a significant decline in prices relatively to the week before demonetization. We analyze this in the section on "Impact on prices".

<sup>&</sup>lt;sup>41</sup>We re-estimate these regressions using maximum value of trade computed as the product of maximum prices and arrivals. Our findings remain the same.

 $<sup>^{42}</sup>$ See Section 2.1 for details.

saw lower impact on prices relative to perishables. Dry chilli prices fell by 9% immediately after demonetization, but recovered after 15 days. Other commodities such as soyabean and tur seed saw a decline of 2-4% in prices in the period following demonetization, but recovered after a week. The evidence on prices along with the sharp decline in arrivals shows the supply side impact that dominated for non perishable commodities.

Perishables, where storing is not an option, saw significant impacts on prices due to demonetization. In the week following the announcement, the decline in the prices of perishables was in the range of 1-16%. It worsened in the week thereafter, with the impacts being significantly large for cauliflower (29-34%). Other commodities like Brinjal, Lime also saw a decline in prices in the range of 10-16%. The fall in prices of perishables with no impact on arrivals could be attributed to demand contraction.

#### Table 6 Weekly changes in arrivals prior and post demonstration

The table presents one and two weeks changes in arrivals vis-a-vis the week prior demonetization. Columns 2 and 3 show the change for 2016-17, that is the year of demonetization. The next two columns show the average change around the same date for the remaining years. Since Diwali can have a significant impact on arrivals, the weekly changes for the remaining years are also shown by excluding the impact of Diwali (Column 6 and 7). This is done by excluding three days prior and three days post Diwali if the date of Diwali falls within the weeks analyzed around demonetization. The last columns shows the proportion of arrivals that come during the *kharif* season for each of the sample commodities. All values are presented as percentage of arrivals in the week prior demonetization.

	Treatment y	year (2016-17)	Control years	s (with Diwali)	Control year	rs (w/o Diwali)	Kharif
Commodity	Post 1 week	Post 2 weeks	Post 1 week	Post 2 weeks	Post 1 week	Post 2 weeks	arrivals
Paddy	-41.51	-29.57	-33.71	-29.84	-36.43	-37.99	76.75
Maize	-43.14	-8.48	-13.02	34.03	7.93	23.21	56.25
Bajra	-54.75	-31.91	-3.39	27.27	-2.13	7.30	50.28
Jowar	-66.84	-54.97	-8.45	42.35	13.80	28.15	37.88
Rice	-15.81	24.62	4.01	43.33	9.07	34.92	35.58
Ragi	-13.69	-17.32	-3.81	14.54	12.67	2.81	35.49
Wheat	-42.11	-44.81	-2.92	30.26	-0.89	3.33	9.46
Soyabean	-86.82	-77.50	-13.82	20.33	-6.57	-7.22	63.03
Groundnut	-55.40	-33.23	17.98	64.64	-1.87	16.55	56.63
Mustard	-47.39	-44.68	-4.67	21.14	-2.87	-5.33	16.54
Dry Chilli	-11.55	28.03	-9.01	33.22	7.05	35.88	24.48
Turmeric	-55.75	-54.21	62.34	152.65	72.45	153.28	19.30
Coriander seed	-81.20	-74.96	1.64	72.09	21.66	20.60	17.81
Cumin	-89.11	-49.74	65.49	266.80	20.47	126.28	14.25
Tur	-34.03	4.95	-11.87	19.12	-5.14	15.91	34.66
Bengal Gram	-69.01	-50.02	-6.96	42.60	6.44	12.20	17.75
-							
Copra	-47.31	-13.03	1.47	26.61	-11.69	1.47	41.22
Arecanut	-32.06	9.84	1.91	58.11	11.97	50.15	40.58
Cashewnuts	-25.97	26.99	23.78	27.68	36.29	39.52	6.95
Cotton	-30.11	3.13	11.91	55.10	5.15	29.81	64.16
Orange	13.51	-49.82	14.48	27.18	-2.68	25.74	73.25
Guava	102.75	157.10	36.61	115.16	81.52	116.98	49.16
Apple	-8.03	-32.68	33.76	99.96	23.31	55.78	47.50
Banana	-3.69	35.17	-4.02	5.57	-8.73	-6.92	34.25
Cauliflower	10.42	43.53	8.30	44.89	14.19	45.76	46.05
Cabbage	-2.20	21.66	-1.10	26.48	4.46	24.37	40.51
Potato	0.45	17.22	-0.84	30.36	1.60	25.17	34.52
Brinjal	-7.51	17.09	-4.92	26.63	3.33	29.06	34.50
Onion	-7.63	1.79	4.81	40.88	3.08	21.95	34.05
Tomato	-6.05	20.08	-8.60	19.28	-4.95	15.53	33.10
Okra	-2.82	16.74	-18.36	-4.64	-18.22	-12.13	20.64
Lime	-9.05	-5.10	-13.10	71.07	-19.52	51.59	29.98
Lemon	33.38	4.03	-16.10	11.09	-12.36	16.37	24.31
Sweet Lime	-15.43	-10.77	5.47	26.47	-0.11	9.74	23.23
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		$\mathbb{R}^2$	0.06	0.14	0.16	0.06	0.04	0.19	0.07	0.42	0.19	0.08	0.31	0.14	0.12	0.22	0.13	0.15	0.11	0.21	0.27	0.29	0.25	0.17	0.27	0.04	0.21	0.07	0.05	0.05	0.08	0.06	0.10	0.12	0.15	0.10
	er	Treated	5,257	2,950	1,383	888	2,169	160	3,169	2,016	851	1,187	209	198	227	56	796	1,128	274	500	45	2,486	619	454	1,780	2,084	3,983	3,014	5,502	4,409	4,882	5,012	2,221	220	764	572
	days aft	Obs.	237,536	115,510	82, 122	50,728	124,480	10,461	248, 386	95, 131	50,664	118,082	9,754	11,521	19,572	16,468	45,147	84,002	10,284	19,376	3,037	62, 186	17,998	23,211	106,526	122,687	141,798	121,889	291,166	224,613	260, 220	254, 830	160,042	13,407	59,430	57, 142
	15	SE	(0.05)	(0.06)	(0.08)	(0.07)	(0.03)	(0.13)	(0.04)	(0.09)	(0.1)	(0.06)	(0.11)	(0.19)	(0.15)	(0.27)	(0.09)	(0.06)	(0.08)	(0.07)	(0.16)	(0.07)	(0.09)	(0.12)	(0.04)	(0.03)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.07)	(0.05)	(0.06)
zation		$\beta_3$	0.13	-0.25	-0.39	-0.27	-0.10	-0.05	-0.39	-0.75	-0.18	-0.33	-0.09	-0.35	-1.04	0.11	-0.14	-0.21	-0.06	-0.01	0.08	-0.22	-0.09	0.01	-0.13	-0.02	0.06	0.02	0.02	0.04	-0.02	0.00	-0.07	0.12	-0.08	-0.02
oneti		$\mathbb{R}^2$	0.05	0.13	0.17	0.06	0.03	0.19	0.06	0.42	0.19	0.07	0.31	0.14	0.12	0.22	0.14	0.15	0.10	0.20	0.26	0.29	0.25	0.17	0.28	0.04	0.19	0.06	0.04	0.05	0.08	0.05	0.10	0.12	0.15	0.09
ter dem	er	Treated	2,460	1,268	554	335	1,051	82	1,144	644	362	486	101	93	72	20	309	442	138	241	25	1,138	293	200	889	1,002	1,904	1,424	2,651	2,158	2,309	2,445	1,110	112	368	296
io 25 af	days afte	Obs.	219,866	106, 339	76,547	47,196	117,521	9,945	234,550	87,074	46,681	112, 173	9,143	10,894	18,378	15,585	42,857	79,694	9,640	18,235	2,899	53,870	15, 139	21,280	100,219	115,976	130,308	113,278	274,920	212,151	245, 357	240,794	154,613	12,749	56,623	54,514
t 1 t	4	SE	(0.05)	(0.07)	(0.11)	(0.09)	(0.03)	(0.18)	(0.05)	(0.13)	(0.11)	(0.07)	(0.12)	(0.34)	(0.17)	(0.23)	(0.1)	(0.07)	(0.08)	(0.07)	(0.18)	(0.07)	(0.09)	(0.1)	(0.05)	(0.04)	(0.03)	(0.03)	(0.02)	(0.02)	(0.02)	(0.02)	(0.04)	(0.08)	(0.07)	(0.06)
en de		$\beta_3$	-0.01	-0.34	-0.50	-0.38	-0.08	-0.27	-0.40	-0.81	-0.34	-0.25	-0.14	-0.38	-0.98	0.23	-0.17	-0.18	-0.07	0.01	-0.06	-0.19	-0.04	0.03	-0.05	-0.02	0.01	0.04	0.05	0.02	0.01	-0.01	-0.09	0.12	-0.04	-0.01
betwe		$\mathbb{R}^2$	0.05	0.12	0.17	0.06	0.03	0.19	0.06	0.41	0.18	0.07	0.32	0.14	0.12	0.22	0.14	0.15	0.11	0.20	0.27	0.29	0.25	0.18	0.29	0.04	0.18	0.06	0.04	0.05	0.08	0.05	0.09	0.12	0.15	0.08
odities		Treated	701	406	187	119	289	31	353	213	115	140	34	34	25	12	104	139	41	71	5 C	332	79	53	254	285	516	411	749	622	682	676	338	39	113	91
s comm	day afte	Obs.	207,848	101,021	73,276	45,311	112,628	9,602	226,684	82, 835	44,379	108,472	8,745	10,467	17,743	15, 122	41,521	77,042	9,208	17,545	2,800	49,054	13,288	20,104	95,649	111,279	122,493	107,500	263,628	203, 328	235, 340	230,943	150,545	12,296	54,681	52,564
acros	-	SE	(0.06)	(0.09)	(0.1)	(0.13)	(0.04)	(0.23)	(0.06)	(0.13)	(0.16)	(0.08)	(0.14)	(0.46)	(0.22)	(0.27)	(0.11)	(0.09)	(0.13)	(0.1)	(0.26)	(0.08)	(0.1)	(0.12)	(0.06)	(0.05)	(0.03)	(0.04)	(0.03)	(0.03)	(0.03)	(0.03)	(0.05)	(0.11)	(0.09)	(0.09)
rivals		$\beta_3$	0.01	-0.19	-0.53	-0.19	-0.09	-0.11	-0.14	-0.46	-0.27	-0.30	-0.21	-0.43	-0.77	0.31	-0.16	-0.04	0.00	-0.02	0.42	-0.03	0.12	0.09	0.01	-0.04	0.02	0.03	0.04	0.03	0.01	0.02	-0.08	0.25	-0.07	0.01
le 7 Impact on ar			Paddy	Maize	Bajra	Jowar	Rice	Ragi	Wheat	Soyabean	Groundnut	Mustard	Dry Chilli	Turmeric	Coriander seed	Cumin	Arhar	BengalGram	Copra	Arecanut	Cashewnuts	Cotton	Orange	Guava	Apple	Banana	Cauliflower	Cabbage	Potato	Brinjal	Onion	Tomato	Okra	Lime	Lemon	Sweet Lime
Tabl																																				

		22	day afte	r			30	0 days aft	ter			4	5 days aft	cer	
B		SE	Obs.	Treated	$\mathbb{R}^2$	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$
0.1	18 ((	(50.05)	251,713	7,609	0.07	0.17	(0.05)	268,662	10,530	0.07	0.17	(0.05)	300,075	15,759	0.08
-0	22 ((	0.06)	123,116	4,464	0.15	-0.21	(0.05)	132,073	6,334	0.15	-0.23	(0.05)	148,300	9,516	0.15
- -	32 ((	0.08)	86,801	2,212	0.16	-0.31	(0.07)	92,444	3,295	0.15	-0.30	(0.07)	102,420	5,177	0.14
- -	25 ((	0.07)	53,746	1,438	0.06	-0.24	(0.07)	57, 395	2,145	0.06	-0.26	(0.02)	64,003	3,389	0.05
-0-	10 ((	0.03)	130, 433	3,127	0.04	-0.10	(0.03)	137,467	4,212	0.04	-0.10	(0.03)	150, 194	6,147	0.04
-0.0	00 (i	0.12)	10,890	222	0.19	-0.06	(0.12)	11,386	304	0.20	-0.07	(0.11)	12,413	494	0.20
-0-	32 ((	0.04)	260,050	5,175	0.07	-0.32	(0.04)	274,091	7,685	0.07	-0.32	(0.04)	299,332	12,061	0.07
-0-	57 ((	0.07)	101,595	3,304	0.42	-0.57	(0.02)	109,458	5,066	0.42	-0.58	(0.02)	123, 277	7,953	0.41
it -0.6	05 (	(0.1)	53,964	1,350	0.20	-0.06	(0.1)	57,868	1,987	0.20	-0.09	(0.00)	64,847	3,098	0.19
-0-	28 ((	0.06)	123,054	1,914	0.08	-0.28	(0.06)	129, 157	2,841	0.08	-0.28	(0.06)	140,245	4,588	0.08
-0-	12 ((	(12)	10,248	299	0.29	-0.11	(0.12)	10,870	423	0.28	-0.09	(0.12)	12,017	614	0.27
-0-	34 ((	(1.17)	12,060	289	0.13	-0.34	(0.17)	12,681	391	0.13	-0.33	(0.17)	13,830	581	0.12
seed -0.8	83 ((	(12)	20,580	433	0.13	-0.83	(0.11)	21,839	713	0.13	-0.83	(0.11)	24,087	1,214	0.14
0.2	24 ((	(3.28)	17,221	114	0.22	0.24	(0.28)	18,174	215	0.22	0.21	(0.28)	19,924	419	0.22
-0-	10 ((	(60.C	47,135	1,240	0.13	-0.12	(0.09)	49,819	1,866	0.12	-0.14	(0.09)	55,769	3,202	0.11
am   -0.	16 ((	0.06)	87,604	1,769	0.15	-0.17	(0.06)	91,903	2,567	0.15	-0.18	(0.06)	99,679	3,956	0.16
-0.0	05 ((	0.08)	10,802	386	0.11	-0.05	(0.08)	11,407	517	0.11	-0.05	(0.02)	12,581	769	0.11
-0-	01 ((	0.07)	20, 329	717	0.21	-0.01	(0.07)	21,435	985	0.21	-0.00	(0.07)	23,507	1,455	0.21
us = 0.1	15 ((	0.16)	3,148	63	0.28	0.15	(0.16)	3,265	83	0.28	0.14	(0.15)	3,482	117	0.29
-0-	23 ((	0.07)	69, 394	3,755	0.29	-0.25	(0.02)	78,293	5,409	0.28	-0.26	(0.02)	94,929	8, 349	0.27
-0-	10 (	(0.1)	20,367	916	0.25	-0.11	(0.1)	23,349	1,279	0.24	-0.15	(0.1)	28,599	1,910	0.23
-0.0	05 ((	0.13)	24,955	693	0.17	-0.07	(0.13)	27,396	984	0.17	-0.10	(0.13)	32,017	1,536	0.16
-0-	15 ((	0.04)	111,560	2,487	0.26	-0.15	(0.04)	117,479	3,273	0.26	-0.16	(0.04)	128, 312	4,783	0.26
-0.0	02 ((	0.03)	128,169	2,943	0.04	-0.02	(0.03)	134,639	3,941	0.04	-0.02	(0.03)	146, 390	5,748	0.05
er   0.0	)5 ((	0.03)	151, 477	5,726	0.21	0.05	(0.03)	163, 192	7,800	0.22	0.05	(0.03)	184,985	11,626	0.22
0.0	)) 00	0.03)	129, 176	4,339	0.07	0.00	(0.03)	138,093	5,918	0.08	-0.00	(0.03)	154, 816	8,842	0.09
0.0	)) 00	0.02)	304,789	7,822	0.05	0.01	(0.02)	321,467	10,612	0.05	0.01	(0.02)	352, 251	15,675	0.05
0.0	)4 ((	0.02)	234,753	6,230	0.05	0.04	(0.02)	246,834	8,375	0.05	0.04	(0.02)	268, 176	12,215	0.05
-0.0	02 ((	0.02)	272,657	6,954	0.07	-0.02	(0.02)	287, 807	9,411	0.07	-0.02	(0.02)	315,783	13,962	0.07
0.0	)] ((	0.02)	266,469	7,081	0.06	0.00	(0.02)	281,009	9,590	0.06	0.00	(0.02)	308,067	14, 140	0.06
-0.0	)) 90	0.04)	164, 185	3,068	0.11	-0.05	(0.04)	168,804	4,030	0.11	-0.05	(0.04)	177,043	5,647	0.11
0.1	10 ((	0.08)	13,977	310	0.11	0.09	(0.08)	14,600	401	0.11	0.08	(0.08)	15,748	569	0.11
-0-	)) 60	0.05)	61,753	1,081	0.15	-0.09	(0.05)	$64,\!469$	1,462	0.15	-0.09	(0.05)	69,267	2,177	0.15
ie 0.0	)2 ((	(90.C	59,112	260	0.10	0.02	(0.06)	61, 375	0.00000000000000000000000000000000000	0.11	0.02	(0.06)	65, 256	1,321	0.13

<b>Table 9</b> Impact on a	rrivals	acros	s comm	odities	betw	een da	ays 60	to 120	after de	nom	etizat	ion				
		9	0 day aft	er			6	) days aft	er			12	0 days af	ter		
	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	
Paddy	0.17	(0.05)	328,470	20,302	0.08	0.16	(0.05)	383,145	29,444	0.08	0.16	(0.05)	431,679	37,308	0.08	
Maize	-0.24	(0.05)	162,984	12, 138	0.15	-0.25	(0.05)	191,873	17,928	0.14	-0.26	(0.05)	218,685	23,261	0.13	
Bajra	-0.30	(0.07)	111,663	6,668	0.13	-0.28	(0.07)	129,577	10,059	0.13	-0.28	(0.07)	147, 227	13,342	0.13	
Jowar	-0.27	(0.07)	70,101	4,406	0.05	-0.28	(0.06)	82,124	6,714	0.05	-0.28	(0.06)	94,369	9,142	0.05	
Rice	-0.11	(0.03)	162, 163	7,756	0.04	-0.11	(0.03)	187,883	11,656	0.04	-0.11	(0.03)	213,823	15,576	0.04	
Ragi	-0.06	(0.11)	13,472	069	0.20	-0.05	(0.11)	15,601	1,021	0.20	-0.03	(0.11)	17,967	1,384	0.19	
Wheat	-0.33	(0.04)	322,648	15,696	0.08	-0.33	(0.04)	370,754	24,353	0.10	-0.32	(0.04)	420,768	33,865	0.09	
Soyabean	-0.60	(0.07)	135,506	10,397	0.40	-0.60	(0.07)	160, 310	15,939	0.38	-0.61	(0.07)	183, 236	21,156	0.36	
Groundnut	-0.11	(0.09)	71,181	4,093	0.18	-0.11	(0.09)	83,388	6,221	0.17	-0.11	(0.09)	95,109	8,427	0.15	
Mustard	-0.28	(0.06)	150,442	5,938	0.08	-0.27	(0.06)	172, 237	9,718	0.08	-0.24	(0.06)	200,154	15,082	0.10	
Dry Chilli	-0.08	(0.13)	13, 120	262	0.25	-0.09	(0.13)	15,388	1,203	0.25	-0.09	(0.14)	17,899	1,630	0.23	
Turmeric	-0.33	(0.17)	14,943	761	0.12	-0.32	(0.17)	17,288	1,190	0.11	-0.32	(0.17)	19,860	1,632	0.12	
Coriander seed	-0.82	(0.11)	26,173	1,635	0.15	-0.81	(0.11)	30,754	2,612	0.15	-0.73	(0.11)	37,140	3,992	0.23	
Cumin	0.22	(0.29)	21,598	616	0.22	0.19	(0.29)	24,743	1,125	0.22	0.22	(0.29)	28,864	1,898	0.22	
Arhar	-0.15	(0.09)	63,492	4,770	0.13	-0.12	(0.09)	83,109	9,427	0.19	-0.06	(0.09)	103,546	14,764	0.22	
$\operatorname{BengalGram}$	-0.19	(0.06)	107, 277	5,055	0.16	-0.20	(0.06)	125,581	8,039	0.15	-0.16	(0.06)	149,385	13,276	0.16	
Copra	-0.04	(0.07)	13,679	1,006	0.11	-0.05	(0.07)	15,944	1,537	0.11	-0.06	(0.07)	18, 349	2,084	0.10	
Arecanut	0.01	(0.07)	25,688	1,905	0.21	0.02	(0.07)	30,283	2,921	0.22	0.03	(0.07)	35,069	3,989	0.21	
Cashewnuts	0.13	(0.15)	3,685	152	0.32	0.14	(0.16)	4,214	240	0.29	0.15	(0.16)	5,229	491	0.22	
Cotton	-0.27	(0.07)	110,257	10,782	0.26	-0.30	(0.07)	141, 198	16,221	0.24	-0.30	(0.07)	170, 226	21,453	0.22	
Orange	-0.16	(0.1)	32,555	2,340	0.21	-0.18	(0.1)	39,939	3,388	0.20	-0.19	(0.1)	49,578	5,049	0.17	
Guava	-0.12	(0.13)	36,096	1,966	0.16	-0.14	(0.13)	44,005	2,902	0.15	-0.15	(0.13)	49,007	3,425	0.16	
Apple	-0.16	(0.04)	137,585	5,895	0.26	-0.16	(0.04)	156,824	8,592	0.27	-0.16	(0.04)	176,045	11,380	0.28	
$\operatorname{Banana}$	-0.02	(0.03)	156,587	7,207	0.05	-0.02	(0.03)	178,754	10,788	0.06	-0.01	(0.03)	201,836	14,480	0.06	
Cauliflower	0.04	(0.03)	205,140	14,830	0.21	0.04	(0.03)	249, 346	22,653	0.21	0.04	(0.03)	292,858	30,451	0.20	
Cabbage	-0.00	(0.03)	170,566	11,411	0.09	-0.01	(0.03)	204,455	17,525	0.10	-0.01	(0.03)	238,744	23,722	0.09	
Potato	0.01	(0.02)	380,470	19,803	0.05	0.01	(0.02)	441,496	29,917	0.05	0.01	(0.02)	502, 839	40,226	0.06	
Brinjal	0.04	(0.02)	287,070	15,351	0.05	0.04	(0.02)	326, 451	22,746	0.05	0.04	(0.02)	365,822	30,050	0.05	
Onion	-0.02	(0.02)	341,767	17,821	0.07	-0.02	(0.02)	396,723	27,155	0.07	-0.02	(0.02)	452,019	36,731	0.07	
Tomato	0.00	(0.02)	333,073	17,992	0.06	-0.00	(0.02)	387,077	27,160	0.06	-0.01	(0.02)	441,593	36,502	0.06	
Okra	-0.04	(0.04)	184,580	7,020	0.11	-0.04	(0.04)	200,421	10,150	0.12	-0.04	(0.04)	218,168	13,707	0.12	
Lime	0.08	(0.08)	16,886	723	0.11	0.08	(0.08)	19,162	1,017	0.11	0.08	(0.08)	21,519	1,326	0.11	
Lemon	-0.09	(0.05)	73,487	2,737	0.15	-0.10	(0.05)	82,170	4,121	0.15	-0.10	(0.05)	91,483	5,670	0.15	
Sweet Lime	0.03	(0.06)	68,233	1,575	0.14	0.03	(0.06)	74,671	2,210	0.17	0.04	(0.06)	82,311	3,051	0.18	

able 10 Impact on	arriva	ls acro	IMOD SSC	moditie	s betu	ween (	lays 1	50  to  2.	33 after	dem	onetiz	ration				
		1.	50 day aft	er			20	0 days af	ter			23	3 days af	ter		
	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	
Paddy	0.16	(0.05)	472,891	43,917	0.08	0.16	(0.05)	541,008	55,650	0.07	0.17	(0.05)	590,164	63,428	0.07	
Maize	-0.26	(0.05)	242,661	27,770	0.12	-0.25	(0.05)	282,878	35,999	0.11	-0.26	(0.06)	311,621	41,167	0.11	
Bajra	-0.27	(0.07)	161,984	15,986	0.14	-0.26	(0.07)	187,912	20,988	0.13	-0.27	(0.02)	207,629	24,688	0.12	
Jowar	-0.28	(0.07)	104,753	11,255	0.05	-0.28	(0.07)	122, 337	14,757	0.05	-0.29	(0.07)	136,548	17, 127	0.05	
Rice	-0.11	(0.03)	239, 371	19,426	0.04	-0.11	(0.03)	281,936	26, 325	0.03	-0.11	(0.03)	311,939	31, 316	0.03	
Ragi	-0.02	(0.12)	20,357	1,783	0.18	0.05	(0.13)	24,560	2,518	0.17	0.04	(0.13)	27,306	2,974	0.17	
Wheat	-0.30	(0.04)	471,676	43,773	0.13	-0.29	(0.04)	592,862	66,091	0.23	-0.29	(0.04)	659,978	78,337	0.22	
Soyabean	-0.62	(0.07)	200,051	24,941	0.35	-0.60	(0.07)	230,448	31,512	0.35	-0.60	(0.07)	252,982	35,151	0.34	
Groundnut	-0.11	(0.1)	105,200	10,093	0.14	-0.11	(0.1)	122,616	12,951	0.13	-0.14	(0.1)	136,677	15,059	0.12	
Mustard	-0.21	(0.06)	232,143	20,943	0.19	-0.17	(0.06)	290,280	30,977	0.23	-0.17	(0.06)	326,463	36,928	0.22	
Dry Chilli	-0.11	(0.14)	20,255	1,992	0.21	-0.11	(0.14)	23,932	2,599	0.19	-0.13	(0.13)	26,467	3,003	0.18	
Turmeric	-0.30	(0.16)	22,517	2,106	0.12	-0.29	(0.17)	27,254	3,055	0.14	-0.29	(0.17)	30,635	3,673	0.14	
Coriander seed	-0.67	(0.12)	43,197	5,187	0.28	-0.64	(0.12)	53,469	7,344	0.28	-0.66	(0.12)	59,836	8,430	0.27	
Cumin	0.22	(0.29)	33,509	2,714	0.33	0.26	(0.29)	42,516	4,116	0.35	0.27	(0.29)	48,018	4,843	0.33	
Arhar	-0.05	(0.1)	120,720	19,231	0.22	-0.01	(0.1)	148, 424	26,211	0.21	0.01	(0.1)	165, 268	30,201	0.20	
BengalGram	-0.13	(0.06)	174,056	19,125	0.20	-0.08	(0.06)	218,500	29,965	0.23	-0.08	(0.06)	246,826	35,976	0.22	
Copra	-0.05	(0.07)	20,522	2,592	0.10	-0.05	(0.07)	24,172	3,413	0.10	-0.06	(0.02)	26,818	4,001	0.09	
Arecanut	0.02	(0.07)	39,601	4,976	0.21	0.02	(0.07)	$47,\!429$	6,567	0.20	0.02	(0.07)	53,000	7,655	0.21	
Cashewnuts	0.16	(0.16)	6,744	832	0.22	0.19	(0.17)	10,468	1,559	0.19	0.23	(0.17)	12,018	1,829	0.18	
Cotton	-0.32	(0.07)	192, 337	25,089	0.22	-0.31	(0.07)	218,419	29,379	0.23	-0.30	(0.07)	228, 201	30,795	0.24	
Orange	-0.19	(0.11)	61,398	6,967	0.16	-0.17	(0.11)	72,910	8,760	0.16	-0.17	(0.11)	74,947	9,062	0.16	
Guava	-0.15	(0.13)	51,769	3,654	0.18	-0.15	(0.13)	53,249	3,806	0.19	-0.15	(0.13)	53,903	3,902	0.19	
Apple	-0.16	(0.04)	193,484	13,845	0.30	-0.16	(0.04)	217, 339	17,653	0.32	-0.15	(0.04)	230,947	20,268	0.34	
Banana	-0.01	(0.03)	225, 395	18,073	0.06	-0.01	(0.03)	264,898	24,176	0.06	-0.01	(0.03)	291,665	28,542	0.05	
Cauliflower	0.04	(0.03)	333,705	37, 385	0.18	0.06	(0.03)	380, 453	45,504	0.19	0.06	(0.03)	404,406	50,059	0.20	
Cabbage	-0.02	(0.03)	271,725	29,485	0.09	-0.01	(0.03)	315, 421	37,145	0.08	-0.01	(0.03)	341,300	41,889	0.09	
Potato	0.01	(0.02)	563,900	50, 321	0.05	0.01	(0.02)	662, 197	67,052	0.05	0.02	(0.02)	729, 798	78,999	0.06	
Brinjal	0.04	(0.02)	406,861	37, 473	0.05	0.04	(0.02)	482, 345	50,536	0.05	0.04	(0.02)	532,980	59,265	0.04	
Onion	-0.02	(0.02)	507, 311	45,938	0.07	-0.02	(0.02)	602, 236	61,925	0.07	-0.02	(0.02)	667, 484	73,213	0.07	
Tomato	-0.01	(0.02)	$495,\!230$	45,645	0.05	-0.01	(0.02)	584,716	60,989	0.05	-0.01	(0.02)	644,557	71,566	0.05	
Okra	-0.04	(0.04)	239, 395	18,060	0.12	-0.06	(0.04)	292,618	28,032	0.12	-0.07	(0.04)	335,816	35,475	0.11	
Lime	0.07	(0.08)	23,989	1,658	0.11	0.07	(0.08)	28,405	2,312	0.11	0.06	(0.08)	31,755	2,800	0.10	
Lemon	-0.10	(0.05)	101,242	7,181	0.14	-0.12	(0.05)	121,696	10,379	0.14	-0.12	(0.05)	137, 362	12,767	0.15	
Sweet Lime	0.05	(0.06)	91,502	4,098	0.17	0.05	(0.06)	108,674	6,282	0.15	0.05	(0.06)	119,972	7,765	0.14	

		$\mathbb{R}^2$	0.50	0.48	0.67	0.33	0.49	0.73	0.74	0.63	0.32	0.76	0.51	0.46	0.69	0.34	0.70	0.83	0.79	0.57	0.29	0.24	0.37	0.43	0.35	0.37	0.45	0.41	0.78	0.35	0.81	0.45	0.24	0.36	0.48	0.49
	er	Treated	5,257.00	2,950.00	1,383.00	888.00	2,169.00	160.00	3,169.00	2,016.00	851.00	1,187.00	209.00	198.00	227.00	56.00	796.00	1,128.00	274.00	500.00	45.00	2,486.00	619.00	454.00	1,780.00	2,084.00	3,983.00	3,014.00	5,502.00	4,409.00	4,882.00	5,012.00	2,221.00	220.00	764.00	572.00
	i days aft	Obs.	237, 536	115,510	82, 122	50,728	124,480	10,461	248, 386	95, 131	50,664	118,082	9,754	11,521	19,572	16,468	45,147	84,002	10,284	19,376	3,037	62, 186	17,998	23,211	106,526	122,687	141,798	121,889	291,166	224,613	260, 220	254, 830	160,042	13,407	59,430	57, 142
	15	SE	(0)	0	(0.01)	(0.01)	0	(0.03)	0	(0.01)	(0.02)	0	(0.03)	(0.02)	(0.02)	(0.03)	(0.01)	(0.01)	(0.02)	(0.02)	(0.03)	(0.01)	(0.07)	(0.05)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.06)	(0.02)	(0.02)
cation		$\beta_3$	0.00	0.01	0.02	0.03	-0.00	0.05	0.01	-0.01	0.00	-0.00	-0.02	0.01	-0.04	-0.08	-0.03	-0.02	0.01	0.00	0.00	0.04	0.05	-0.13	0.02	-0.01	-0.29	-0.05	-0.09	-0.14	0.17	-0.05	-0.07	-0.11	-0.04	-0.00
onetiz		$\mathbb{R}^2$	0.51	0.47	0.67	0.33	0.49	0.73	0.75	0.64	0.32	0.76	0.52	0.46	0.69	0.34	0.70	0.84	0.80	0.57	0.28	0.24	0.37	0.43	0.35	0.37	0.40	0.40	0.78	0.35	0.81	0.44	0.23	0.36	0.48	0.49
ter dem	er	Treated	2,460.00	1,268.00	554.00	335.00	1,051.00	82.00	1,144.00	644.00	362.00	486.00	101.00	93.00	72.00	20.00	309.00	442.00	138.00	241.00	25.00	1,138.00	293.00	200.00	889.00	1,002.00	1,904.00	1,424.00	2,651.00	2,158.00	2,309.00	2,445.00	1,110.00	112.00	368.00	296.00
to 25 af	r days aft	Obs.	219,866	106, 339	76,547	47,196	117,521	9,945	234,550	87,074	46,681	112, 173	9,143	10,894	18,378	15,585	42,857	79,694	9,640	18,235	2,899	53,870	15, 139	21,280	100, 219	115,976	130, 308	113,278	274,920	212,151	245, 357	240,794	154,613	12,749	56,623	54,514
ays 1		SE	(0)	(0.01)	(0.01)	(0.01)	0	(0.02)	0	(0.01)	(0.02)	0	(0.03)	(0.01)	(0.03)	(0.04)	(0.02)	(0.01)	(0.02)	(0.02)	(0.02)	(0.01)	(0.05)	(0.05)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.01)	(0.01)	(0.01)	(0.02)	(0.07)	(0.03)	(0.03)
een da		$\beta_3$	0.00	0.01	0.00	0.04	-0.00	0.05	-0.01	-0.03	-0.00	0.00	-0.04	0.03	-0.00	-0.08	-0.02	0.02	0.02	0.01	0.04	0.04	0.01	-0.11	0.01	-0.01	-0.14	-0.03	-0.06	-0.09	0.11	-0.06	-0.02	-0.16	-0.01	0.02
betw		$\mathbb{R}^2$	0.52	0.47	0.67	0.33	0.49	0.73	0.74	0.64	0.32	0.76	0.52	0.45	0.68	0.34	0.71	0.84	0.81	0.58	0.27	0.23	0.37	0.43	0.36	0.37	0.37	0.40	0.78	0.34	0.82	0.43	0.23	0.36	0.49	0.50
nodities	er	Treated	701.00	406.00	187.00	119.00	289.00	31.00	353.00	213.00	115.00	140.00	34.00	34.00	25.00	12.00	104.00	139.00	41.00	71.00	5.00	332.00	79.00	53.00	254.00	285.00	516.00	411.00	749.00	622.00	682.00	676.00	338.00	39.00	113.00	91.00
ss comm	l day afte	Obs.	207,848	101,021	73,276	45,311	112,628	9,602	226,684	82, 835	44,379	108,472	8,745	10,467	17,743	15,122	41,521	77,042	9,208	17,545	2,800	49,054	13,288	20,104	95,649	111,279	122,493	107,500	263,628	203, 328	235, 340	230,943	150,545	12,296	54,681	52,564
acros		SE	(0)	(0.01)	(0.01)	(0.02)	(0.01)	(0.04)	(0.01)	(0.02)	(0.02)	0	(0.05)	(0.02)	(0.03)	(0.05)	(0.02)	(0.02)	(0.03)	(0.03)	(0.02)	(0.01)	(0.06)	(0.06)	(0.02)	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.01)	(0.01)	(0.02)	(0.09)	(0.04)	(0.03)
prices		$\beta_3$	0.01	-0.00	-0.00	0.04	-0.00	0.07	-0.00	-0.04	0.02	0.01	-0.09	-0.00	-0.03	-0.06	-0.04	0.00	0.03	0.02	0.03	0.02	-0.07	0.00	0.00	0.00	-0.08	-0.04	-0.03	-0.07	0.09	-0.07	-0.00	-0.14	-0.05	0.05
<b>11</b> Impact on			Paddy	Maize	Bajra	Jowar	Rice	Ragi	Wheat	Soyabean	Groundnut	Mustard	Dry Chilli	Turmeric	Coriander seed	Cumin	Arhar	BengalGram	Copra	Arecanut	Cashewnuts	Cotton	Orange	Guava	Apple	Banana	Cauliflower	Cabbage	Potato	Brinjal	Onion	Tomato	Okra	Lime	Lemon	Sweet Lime
Table																																				

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z impact on p	20011															
		5	2 day aft€	er (			30	days aft	er			4	5 days aft	er		
<u> </u>	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	
ddy .	-0.00	(0)	251,713	7,609	0.49	-0.00	(0)	268,662	10,530	0.49	-0.00	(0)	300,075	15,759	0.49	
uize	0.01	(0)	123, 116	4,464	0.48	0.01	(0)	132,073	6,334	0.48	0.01	(0)	148,300	9,516	0.48	
jra	0.02	(0.01)	86,801	2,212	0.67	0.02	(0.01)	92,444	3,295	0.67	0.02	(0.01)	102,420	5,177	0.67	
var	0.03	(0.01)	53,746	1,438	0.32	0.03	(0.01)	57, 395	2,145	0.32	0.03	(0.01)	64,003	3,389	0.31	
	-0.01	0)	130, 433	3,127	0.49	-0.01	0	137,467	4,212	0.49	-0.01	(0)	150, 194	6,147	0.49	
	0.05	(0.03)	10,890	222	0.73	0.05	(0.03)	11,386	304	0.74	0.05	(0.03)	12,413	494	0.75	
leat	0.01	0	260,050	5,175	0.75	0.01	0	274,091	7,685	0.76	0.01	(0)	299,332	12,061	0.76	
abean .	-0.00	(0)	101,595	3,304	0.63	-0.00	(0)	109,458	5,066	0.63	-0.00	(0)	123, 277	7,953	0.63	
oundnut	0.01	(0.01)	53,964	1,350	0.33	0.01	(0.01)	57,868	1,987	0.33	0.01	(0.01)	64,847	3,098	0.33	
istard .	-0.00	(0)	123,054	1,914	0.76	-0.00	(0)	129, 157	2,841	0.75	-0.00	(0)	140,245	4,588	0.74	
y Chilli	-0.03	(0.03)	10,248	299	0.51	-0.02	(0.03)	10,870	423	0.50	-0.02	(0.03)	12,017	614	0.49	
rmeric	0.01	(0.02)	12,060	289	0.47	0.01	(0.02)	12,681	391	0.47	0.01	(0.02)	13,830	581	0.48	
riander seed	-0.03	(0.02)	20,580	433	0.69	-0.03	(0.02)	21,839	713	0.69	-0.03	(0.02)	24,087	1,214	0.69	
	-0.04	(0.03)	17,221	114	0.34	-0.04	(0.03)	18,174	215	0.34	-0.03	(0.03)	19,924	419	0.34	
har .	-0.04	(0.01)	47,135	1,240	0.70	-0.03	(0.01)	49,819	1,866	0.71	-0.03	(0.01)	55,769	3,202	0.71	
ngalGram .	-0.02	(0.01)	87,604	1,769	0.83	-0.02	(0.01)	91,903	2,567	0.83	-0.03	(0.01)	99,679	3,956	0.83	
pra	0.01	(0.02)	10,802	386	0.79	0.01	(0.02)	11,407	517	0.79	0.02	(0.02)	12,581	769	0.78	
ecanut .	-0.00	(0.02)	20,329	717	0.56	-0.00	(0.02)	21,435	985	0.56	-0.00	(0.02)	23,507	1,455	0.56	
shewnuts	0.01	(0.03)	3,148	63	0.29	0.01	(0.03)	3,265	83	0.30	0.01	(0.03)	3,482	117	0.31	
tton	0.05	(0.01)	69, 394	3,755	0.24	0.04	(0.01)	78,293	5,409	0.25	0.04	(0.01)	94,929	8,349	0.27	
ange	0.10	(0.08)	20,367	916	0.36	0.11	(0.08)	23,349	1,279	0.37	0.11	(0.09)	28,599	1,910	0.41	
ava .	-0.11	(0.05)	24,955	693	0.43	-0.11	(0.05)	27,396	984	0.42	-0.11	(0.05)	32,017	1,536	0.41	
ple	0.02	(0.02)	111,560	2,487	0.34	0.02	(0.02)	117,479	3,273	0.34	0.02	(0.02)	128, 312	4,783	0.34	
nana .	-0.02	(0.01)	128,169	2,943	0.37	-0.02	(0.01)	134,639	3,941	0.37	-0.02	(0.01)	146, 390	5,748	0.37	
uliflower .	-0.34	(0.02)	151,477	5,726	0.47	-0.34	(0.02)	163, 192	7,800	0.50	-0.33	(0.02)	184,985	11,626	0.53	
ubbage .	-0.04	(0.02)	129, 176	4,339	0.41	-0.04	(0.02)	138,093	5,918	0.41	-0.04	(0.02)	154, 816	8,842	0.44	
otato .	-0.13	(0.01)	304,789	7,822	0.77	-0.13	(0.01)	321,467	10,612	0.76	-0.13	(0.01)	352, 251	15,675	0.75	
injal .	-0.16	(0.02)	234,753	6,230	0.34	-0.16	(0.02)	246,834	8,375	0.35	-0.16	(0.02)	268, 176	12,215	0.36	
nion	0.19	(0.01)	272,657	6,954	0.80	0.19	(0.01)	287,807	9,411	0.80	0.19	(0.01)	315,783	13,962	0.79	
mato .	-0.04	(0.01)	266,469	7,081	0.46	-0.04	(0.01)	281,009	9,590	0.47	-0.04	(0.01)	308,067	14, 140	0.49	
ra.	-0.07	(0.02)	164, 185	3,068	0.24	-0.07	(0.02)	168,804	4,030	0.25	-0.08	(0.02)	177,043	5,647	0.26	
ne .	-0.10	(0.07)	13,977	310	0.35	-0.10	(0.07)	14,600	401	0.35	-0.11	(0.07)	15,748	569	0.35	
. non	-0.06	(0.02)	61,753	1,081	0.48	-0.06	(0.02)	64, 469	1,462	0.48	-0.05	(0.02)	69, 267	2,177	0.48	
veet Lime	-0.01	(0.03)	59,112	260	0.49	-0.01	(0.03)	61,375	026	0.49	-0.01	(0.03)	65, 256	1,321	0.49	

Impact on p	rices	acros	s comm	odities l	betwe	en da	ws 60	to 120	after de	mone	etizati	on				
-		90	) day aft€	er			<u>)6</u>	) days aft	er			12	0 days af	ter		
	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	$\beta_3$	SE	Obs.	Treated	$\mathbb{R}^2$	
-	00.00	(0)	328,470	20,302	0.49	-0.00	(0)	383,145	29,444	0.49	-0.00	(0)	431,679	37,308	0.49	
_	0.01	(0)	162,984	12,138	0.47	0.01	(0)	191,873	17,928	0.47	0.01	0)	218,685	23,261	0.47	
_	0.02	(0.01)	111,663	6,668	0.67	0.02	(0)	129,577	10,059	0.67	0.02	0	147, 227	13,342	0.66	
_	0.04	(0.01)	70,101	4,406	0.31	0.04	(0.01)	82,124	6,714	0.30	0.04	(0.01)	94,369	9,142	0.29	
-	-0.01	(0)	162, 163	7,756	0.48	-0.01	0	187,883	11,656	0.46	-0.01	0)	213,823	15,576	0.44	
	0.05	(0.03)	13,472	069	0.75	0.05	(0.03)	15,601	1,021	0.74	0.06	(0.03)	17,967	1,384	0.76	
_	0.01	(0)	322,648	15,696	0.76	0.01	(0)	370, 754	24,353	0.77	0.01	0)	420,768	33,865	0.76	
_	0.00	(0)	135,506	10,397	0.63	0.00	(0)	160, 310	15,939	0.62	0.00	(0)	183, 236	21,156	0.61	
_	0.01	(0.01)	71,181	4,093	0.33	0.01	(0.01)	83,388	6,221	0.33	0.01	(0.01)	95,109	8,427	0.33	
1	00.0	(0)	150,442	5,938	0.73	-0.00	(0)	172, 237	9,718	0.70	-0.01	(0)	200,154	15,082	0.66	
	-0.01	(0.03)	13, 120	796	0.45	-0.01	(0.03)	15,388	1,203	0.43	-0.01	(0.03)	17,899	1,630	0.42	
_	0.01	(0.02)	14,943	761	0.49	0.00	(0.02)	17,288	1,190	0.49	0.01	(0.02)	19,860	1,632	0.49	
- peed	-0.03	(0.02)	26,173	1,635	0.69	-0.03	(0.02)	30,754	2,612	0.67	-0.04	(0.02)	37,140	3,992	0.66	
	-0.02	(0.03)	21,598	616	0.33	-0.02	(0.03)	24,743	1,125	0.32	-0.02	(0.03)	28,864	1,898	0.31	
	-0.03	(0.01)	63,492	4,770	0.71	-0.03	(0.01)	83,109	9,427	0.73	-0.03	(0.01)	103,546	14,764	0.73	
- m	-0.03	(0.01)	107, 277	5,055	0.83	-0.03	(0.01)	125,581	8,039	0.82	-0.04	(0.01)	149,385	13,276	0.81	
_	0.02	(0.02)	13,679	1,006	0.77	0.02	(0.02)	15,944	1,537	0.76	0.02	(0.02)	18, 349	2,084	0.73	
1	-0.00	(0.02)	25,688	1,905	0.56	-0.00	(0.02)	30,283	2,921	0.54	-0.01	(0.02)	35,069	3,989	0.48	
ts	0.01	(0.03)	3,685	152	0.33	0.01	(0.03)	4,214	240	0.36	0.01	(0.03)	5,229	491	0.44	
	0.04	(0.01)	110,257	10,782	0.29	0.04	(0.01)	141, 198	16,221	0.34	0.04	(0.01)	170,226	21,453	0.37	
_	0.11	(0.09)	32,555	2,340	0.40	0.11	(0.09)	39,939	3,388	0.37	0.11	(0.09)	49,578	5,049	0.34	
-	-0.11	(0.05)	36,096	1,966	0.40	-0.11	(0.05)	44,005	2,902	0.40	-0.11	(0.05)	49,007	3,425	0.41	
	0.02	(0.02)	137,585	5,895	0.34	0.02	(0.02)	156,824	8,592	0.35	0.02	(0.02)	176,045	11,380	0.37	
1	-0.02	(0.01)	156,587	7,207	0.37	-0.02	(0.01)	178,754	10,788	0.36	-0.02	(0.01)	201,836	14,480	0.34	
r	-0.33	(0.02)	205,140	14,830	0.54	-0.33	(0.02)	249, 346	22,653	0.57	-0.32	(0.02)	292,858	30,451	0.58	
	-0.04	(0.02)	170,566	11,411	0.45	-0.03	(0.02)	204,455	17,525	0.49	-0.03	(0.02)	238,744	23,722	0.51	
1	-0.13	(0.01)	380,470	19,803	0.74	-0.13	(0.01)	441,496	29,917	0.74	-0.13	(0.01)	502, 839	40,226	0.73	
1	-0.16	(0.02)	287,070	15,351	0.36	-0.16	(0.02)	326, 451	22,746	0.35	-0.16	(0.02)	365,822	30,050	0.33	
	0.18	(0.01)	341,767	17,821	0.78	0.18	(0.01)	396, 723	27,155	0.77	0.18	(0.01)	452,019	36,731	0.77	
	-0.04	(0.01)	333,073	17,992	0.51	-0.03	(0.01)	387,077	27,160	0.53	-0.03	(0.01)	441,593	36,502	0.53	
-	-0.08	(0.02)	184,580	7,020	0.27	-0.08	(0.02)	200,421	10,150	0.31	-0.09	(0.02)	218,168	13,707	0.34	
	-0.12	(0.07)	16,886	723	0.35	-0.12	(0.08)	19,162	1,017	0.33	-0.12	(0.08)	21,519	1,326	0.32	
	-0.05	(0.02)	73,487	2,737	0.48	-0.05	(0.02)	82,170	4,121	0.46	-0.06	(0.02)	91,483	5,670	0.44	
e e	-0.01	(0.03)	68,233	1,575	0.49	-0.01	(0.03)	74,671	2,210	0.48	-0.01	(0.03)	82,311	3,051	0.46	

ritces across commodities betw 150 day after 2 cr Ots Tester	150 day after	io day after	ter Tracted D2	50			20( CE	) days af	ter	50	0	23 CF	3 days aft	Cer	D2
D. dd	β3 000	З С С	170 001	Treated	47 V	β3 000	SE SE	Ubs.	Treated	H <sup>4</sup>	β3 000	E S	Ubs.	Treated	R <sup>4</sup>
idy ize	-0.00	00	4.72,891 242,661	43,917 $27,770$	0.49 0.46	-0.00	00	241,008 282,878	55,999	$0.49 \\ 0.46$	-0.00	00	390,104 311,621	03,428 $41,167$	$0.48 \\ 0.46$
jra	0.02	0	161,984	15,986	0.65	0.02	0	187,912	20,988	0.65	0.02	0	207,629	24,688	0.65
var	0.04	(0.01)	104,753	11,255	0.29	0.04	(0.01)	122, 337	14,757	0.27	0.04	(0.01)	136,548	17, 127	0.28
e	-0.01	0	239, 371	19,426	0.44	-0.01	0	281,936	26, 325	0.44	-0.01	0)	311,939	31, 316	0.44
gi	0.06	(0.03)	20,357	1,783	0.77	0.06	(0.03)	24,560	2,518	0.78	0.06	(0.03)	27,306	2,974	0.78
neat	0.01	0	471,676	43,773	0.73	0.01	(0)	592,862	66,091	0.69	0.01	0)	659,978	78,337	0.69
yabean	-0.00	0	200,051	24,941	0.61	0.00	0)	230,448	31,512	0.62	0.00	0)	252,982	35,151	0.61
oundnut	0.01	(0.01)	105,200	10,093	0.33	0.01	(0.01)	122,616	12,951	0.33	0.01	(0.01)	136,677	15,059	0.33
ustard	-0.01	0	232,143	20,943	0.63	-0.01	0	290,280	30,977	0.60	-0.01	(0)	326,463	36,928	0.59
y Chilli	-0.01	(0.03)	20,255	1,992	0.42	-0.02	(0.03)	23,932	2,599	0.43	-0.02	(0.03)	26,467	3,003	0.44
urmeric	0.01	(0.02)	22,517	2,106	0.50	0.00	(0.02)	27,254	3,055	0.52	0.00	(0.02)	30,635	3,673	0.53
riander seed	-0.03	(0.02)	43,197	5,187	0.64	-0.03	(0.02)	53,469	7,344	0.63	-0.03	(0.02)	59,836	8,430	0.63
umin	-0.02	(0.03)	33,509	2,714	0.33	-0.03	(0.03)	42,516	4,116	0.36	-0.03	(0.03)	48,018	4,843	0.37
har	-0.03	(0.01)	120,720	19,231	0.73	-0.03	(0.01)	148, 424	26,211	0.74	-0.03	(0.01)	165,268	30,201	0.74
ngalGram	-0.04	(0.01)	174,056	19,125	0.81	-0.04	(0.01)	218,500	29,965	0.81	-0.04	(0.01)	246,826	35,976	0.81
pra	0.03	(0.02)	20,522	2,592	0.74	0.03	(0.02)	24,172	3,413	0.75	0.03	(0.02)	26,818	4,001	0.74
ecanut	-0.00	(0.02)	39,601	4,976	0.45	-0.00	(0.02)	$47,\!429$	6,567	0.44	-0.00	(0.02)	53,000	7,655	0.44
shewnuts	0.01	(0.03)	6,744	832	0.51	0.01	(0.03)	10,468	1,559	0.51	0.01	(0.03)	12,018	1,829	0.52
tton	0.04	(0.01)	192, 337	25,089	0.39	0.04	(0.01)	218,419	29,379	0.38	0.04	(0.01)	228, 201	30,795	0.37
ange	0.11	(0.09)	61, 398	6,967	0.34	0.11	(0.09)	72,910	8,760	0.37	0.11	(0.09)	74,947	9,062	0.38
lava	-0.11	(0.05)	51,769	3,654	0.42	-0.11	(0.05)	53,249	3,806	0.42	-0.11	(0.05)	53,903	3,902	0.42
ple	0.02	(0.02)	193,484	13,845	0.39	0.02	(0.02)	217, 339	17,653	0.43	0.01	(0.02)	230,947	20,268	0.46
nana	-0.02	(0.01)	225, 395	18,073	0.33	-0.02	(0.01)	264,898	24,176	0.32	-0.02	(0.01)	291,665	28,542	0.31
uliflower	-0.32	(0.02)	333,705	37, 385	0.56	-0.32	(0.02)	380, 453	45,504	0.53	-0.33	(0.02)	404,406	50,059	0.53
ubbage	-0.02	(0.02)	271, 725	29,485	0.50	-0.02	(0.02)	315,421	37,145	0.47	-0.02	(0.02)	341,300	41,889	0.46
otato	-0.13	(0.01)	563,900	50, 321	0.72	-0.13	(0.01)	662, 197	67,052	0.70	-0.13	(0.01)	729, 798	78,999	0.69
injal	-0.16	(0.02)	406,861	37, 473	0.30	-0.15	(0.02)	482, 345	50,536	0.28	-0.15	(0.02)	532,980	59,265	0.26
nion	0.18	(0.01)	507, 311	45,938	0.76	0.18	(0.01)	602, 236	61,925	0.76	0.18	(0.01)	667, 484	73,213	0.75
mato	-0.02	(0.01)	$495,\!230$	45,645	0.52	-0.02	(0.01)	584,716	60,989	0.47	-0.02	(0.01)	644,557	71,566	0.45
tra	-0.09	(0.02)	239, 395	18,060	0.35	-0.08	(0.02)	292,618	28,032	0.32	-0.07	(0.02)	335,816	35,475	0.31
ne	-0.12	(0.08)	23,989	1,658	0.35	-0.12	(0.08)	28,405	2,312	0.37	-0.12	(0.08)	31,755	2,800	0.35
mon	-0.06	(0.02)	101,242	7,181	0.45	-0.05	(0.02)	121,696	10,379	0.48	-0.06	(0.02)	137, 362	12,767	0.46
veet Lime	-0.01	(0.03)	91,502	4,098	0.44	-0.01	(0.03)	108,674	6,282	0.43	-0.01	(0.02)	119,972	7,765	0.44