# Demonetization and Healthcare Expenditure *

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**Abstract**

Do liquidity shocks affect healthcare expenditure? The literature does not provide a definitive answer. Herein, a stream of research indicates that health outcomes like mortality rate and other indicators of adverse health may be procyclical. Recent work, however, seems to suggest an absence of a relationship between health and wealth. In this paper, we exploit the sudden demonetization in India in 2016 as a transitory negative liquidity shock, to explore its causal effects on healthcare expenditure. We find that the sales of drugs for unanticipated illnesses (acute) fall relatively more than those for anticipated (chronic) illnesses. Liquidity-driven demand-side contractions are the main driver of the results, as opposed to operational constraints on potentially cash-reliant firms. The effects are heterogeneous within sub-categories of illnesses—the fall in sales shows a correlation with the perception of how urgently the treatment requires the drugs. Our work puts liquidity constraints as a potential mechanism through which macroeconomic shocks may affect healthcare expenditure.

**Keywords:** Liquidity Shocks, Drugs for Acute and Chronic Illnesses, Consumption Choices, Demonetization

**JEL Codes:** I11, I14, E21

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# 1 Introduction

Healthcare expenditure on drugs forms a significant share of household budgets worldwide. How do liquidity shocks affect the decisions on these expenditures? This question is important as a vast majority of households in the poor countries do not have access to the formal insurance markets, and hence, they are often exposed to macroeconomic fluctuations. We have some proximate answers from the literature. Beginning with Ruhm (2000), a stream of research has found recessions to be good for health, with potential explanations being higher opportunity cost of time spent on healthy activities during business cycle crests, higher workplace accidents and general health risk due to the nature of the work. This relationship holds true in further work accounting for regional variations (Ruhm, 2003, 2005, 2016) or during acute crisis (Ruhm, 2016). More recent studies, however, using micro-economic data have found a small or negligible relationship between health and wealth (Acemoglu *et al.*, 2013; Lovenheim & Yun, 2024).

These investigations have often overlooked the heterogeneity of healthcare expenditures due to the different nature of illnesses. Sorensen (2000) describes how the difference in search behaviour for drugs for acute and chronic illnesses leads to variations in the prices of these drugs.[1] Drugs for chronic ailments (chronic drugs) are purchased regularly for frequent consumption for all future periods, compelling consumers to search for and use the cheapest options. On the other hand, acute drugs are consumed due to the unanticipated onset of acute illnesses only for a given period. As such, consumers do not search extensively for the price menu of acute drugs. Since chronic illnesses do not worsen suddenly or remain latent unless checked, demand for chronic drugs at the intensive and extensive margin remains invariant to temporary economic shocks. For acute illnesses, however, cash constraints will push consumers to limit purchases of these drugs as these are likely to be beyond the household budget. Thus, acute drug sales are more likely to experience a steeper drop after a negative liquidity shock.

Understanding this heterogeneity can elucidate the relationship between healthcare expenditure and macroeconomic fluctuations. In this paper, our goal is to explore exactly this relationship. To do that, we bring to the literature a novel addition of drug sales data with state×time×firms×illness level variations in India.

We use the demonetization event in India as an exogenous liquidity shock when nearly 90% of the nation's currency was withdrawn in November 2016 (Chodorow-Reich

[1] Einav *et al.* (2018) demonstrates the variation in price elasticity of these two types of drugs.

*et al.*, 2020). Our data comes from the All India Organization of Chemists and Druggists (AIOCD), which records monthly volume and value of acute and chronic drug sales across 18 illness categories, 31 regions, and 805 pharmaceutical firms from 2015, 2016, and 2017. Controlling for the time-varying region, illness and firm-level effects, we find that the volume of acute drug sales experienced a 4.4% higher decline post-demonetization relative to the sales of chronic drugs. Further, the value of sales declined by nearly 2.6% more compared to the chronic drugs after the liquidity shock. Importantly, we find no changes in the relative prices of these drugs after the liquidity shock.

The above results are consistent with demand-driven contraction wherein households accommodate their expenditure after the liquidity shock. However, a supply-driven contraction due to operational challenges for cash-constrained pharmaceutical firms may also depress sales. If the latter hypothesis is pre-dominant, domestic firms, which are smaller and more cash-reliant, should experience a higher contraction than the MNCs. We find evidence against the supply-driven contraction—the MNC firms experience a higher decline in sales post-cash crunch. Further, the inter-regional heterogeneity of our result is consistent with demand contraction—decline is higher in poorer states where liquidity constraints are more binding.

Across different illnesses, acute drugs for anti-malarial, gastrointestinal and respiratory treatment respond the most to the liquidity shock, while sales for cardiac treatment do not undergo any change. This is expected as patients may find it difficult to reduce expenditure for serious events such as cardiac arrests. A decline in expenditure for treating malaria, even after accounting for seasonality, may also impose serious health consequences, though studying that is beyond the scope of this paper.

We assess the robustness of our results to several additional checks. First, the sales trends of acute and chronic drugs do not diverge before demonetization, ruling out pre-shock factors behind the post-shock effects. Second, we conduct our analysis using a sub-set of control group observations, matched using Propensity Score Matching (Rosenbaum & Rubin, 1985) and Coarsened Exact Matching (Iacus *et al.*, 2012). The results, with either matching process, remain qualitatively unchanged. This makes the results robust to other time-invariant differences between the two groups, which could bias the effect.

Our observations are aggregated at the state-firm-illness level. Each possible cluster has a non-zero share of treatment and control group observations, posing a challenge in *clustering* the standard errors (Abadie *et al.*, 2023). To overcome this limitation,

we conduct Randomization Inference (RI) (Hagemann, 2019). Under this method, we randomly assign the treatment indicator to observations multiple times and measure the pseudo-estimates for each randomization. This process disassociates the treatment assignment to any potential cluster we do not observe. If the original estimate was biased due to confounding factors, the pseudo-estimates from random assignment should not be distinct from the original estimate. These advantages of using RI have been outlined in Conley & Taber (2011) and MacKinnon & Webb (2020). We estimate 50 placebo Average Treatment Effects by randomizing the assignment of the treatment indicator. The original estimate is significantly distinct from the pseudo-estimates distribution, furthering our confidence in our results.

Early research on the intersection of health and the economy inspected whether health was procyclical or counter-cyclical. Pioneering work by Brenner documented a positive relationship between health and aggregate macro-economic variables (Brenner, 1971, 1979; Brenner & Mooney, 1983), even in industrialized countries (Brenner, 1987). However, Ruhm (2016) provides a summary of the shortcomings of this strand of literature. The series of studies by Ruhm, mentioned earlier, indicates the result in the opposite direction. However, Ruhm (2015) casts some doubt on the robustness of countercyclical health, as well. In short, whether health is robustly procyclical or countercyclical remains an open question.

Studies which analyze natural experiments using micro-economic data have mostly yielded small or nearly zero elasticity between healthcare expenses and economic shocks.[2] Acemoglu *et al.* (2013) and Moscone & Tosetti (2010) find a less-than-proportionate response of area-level healthcare expenditure due to local area income shocks in the US. At the household level, Okunade *et al.* (2010) estimate a small elasticity for out-of-pocket health expenditure and wealth in Thailand, measured as a composite variable of assets and landholdings. Lovenheim & Yun (2024), on the other hand, finds no relationship between wealth increase due to higher property prices and health outcomes in the US.

Our paper's main contribution is to causally identify the heterogeneity of the impact of cash constraints on healthcare expenses. Patients use the cheapest option for long-term chronic ailments, leaving little space to reduce expenses under a cash constraint. Further, these ailments worsen gradually over time, where the need to address them remains

[2]A separate literature has explored the relationship in the reverse direction—impact of health shocks on economic outcomes. See Wagstaff (2007); Mitra *et al.* (2016); Houeninvo *et al.* (2023); Leive & Xu (2008) for such analyses for developing countries. Notably, Mohanan (2013) studies the impact on economic outcomes of injuries sustained in bus accidents in India as exogenous health shocks.

unchanged under a short-term economic shock. Cash constraints are more binding for acute drugs since households are less knowledgeable of cheaper substitutes, pushing some households to abandon the purchase during the transition period. Thus, the absence of a strong effect estimated by earlier research may reflect the impact on only chronic drug purchases. In contrast, a negative liquidity shock may significantly depress acute drug expenditure, potentially leading to consequent health effects due to acute illnesses.

The context of our study provides its second contribution. A possible explanation provided by Ruhm (2016) for the countercyclicality of health is reduced accidents and other fatal occurrences because people stay at home during recessions. However, developing countries rarely have a social safety net to allow people to stay home when the market wage falls below the reservation wage. During demonetization, people in India had to queue up at banks to exchange old notes for legal tenders, increasing the risk of infectious diseases. Thus, a reduction in illnesses or fatalities is unlikely to explain the dip in acute drug sales, as we find. In the broader context of developing countries, economic shocks may have more salience owing to high out-of-pocket healthcare expenditure and low insurance penetration (Wagstaff, 2007; Mitra *et al.*, 2016; Houeninvo *et al.*, 2023; Leive & Xu, 2008).

Economic shocks are becoming more prevalent and frequent in today's world of climate risks, wars, pandemics and international conflicts. The withdrawal of nearly 90 per cent of the currency in a still highly cash-reliant economy provides a natural experiment to study the research question. Several papers have demonstrated the salient effects of this shock across the Indian economy (Lahiri, 2020; Wadhwa, 2020; Chodorow-Reich *et al.*, 2020; Dev & Unni, 2024; Das *et al.*, 2023). In addition, this income shock varied across regions depending on the pre-shock income level, and informality—poorer states in the north underwent a higher decline in economic activity. Similar demonetization exercises were conducted in Kenya in 2019 and Nigeria in 2022, which may have caused unintended health consequences (Central Bank of Kenya, 2023). While we use the demonetization episode in India as the negative income shock, the results from our analysis are extendable to such events and other sudden and intense shocks.

The rest of the paper proceeds as follows. In section 2, we develop some basic hypothesis about how income shock may or may not induce expenditure shift across planned and unplanned consumption of medicines. Section 3 describes the data used in our analysis along with the institutional context. We provide empirical illustrations of our arguments in section 4. This discussion is followed by section 5 which sets up the

econometric specifications to test our hypothesis. Section 6 provides all results along with the mechanisms and robustness checks. Finally, section 7 summarizes and concludes. For brevity, we will refer to drugs used for chronic (acute) illnesses as chronic (acute) drugs.

## 2 Healthcare Expenditure and Liquidity Shocks

Health insurance penetration in poor countries has remained persistently low (Hooley *et al.*, 2022), with India being no exception (Ellis *et al.*, 2000). Mavalankar & Bhat (2000) estimate that only 1 million out of the entire population of India has any form of health coverage. This has resulted in high out-of-pocket expenses for medical needs. Jayakrishnan *et al.* (2016) find that while the incidence of ailments increased by 13% between 2004-05 and 2014-15, outpatient and inpatient care expenses increased by more than 100% and 300%, respectively, over the same period. More than 80% of these expenditures were financed out of pocket. Social and economic inequities exacerbate this problem—older and poorer populations in India have experienced a higher increase in medical-related out-of-pocket expenses. Further, households rely on distress sales of assets and borrowing to finance these expenditures (Sangar *et al.*, 2019). Thus, healthcare expenditure holds significant salience for Indian households.

Expenses for medicines may occur due to two broad reasons. First, some conditions develop over time and, once developed, become expected and anticipated. These are known as chronic conditions and require continuous interventions of prescribed and specific dosages. Examples include diabetes, hypertension, thyroid, etc. On the other hand, unanticipated medical conditions become severe quickly. Some common acute illnesses in India are bacterial or viral infections such as dengue, chikungunya, etc. and carrier-led diseases such as malaria.

Sorensen (2000) records the price differential between these two types of drugs and attributes them to the respective search behaviour due to their onset and treatment differences. Specifically, due to the recurring need for chronic drugs, consumers have an incentive to *price-shop* for these drugs enabling them to buy the cheapest possible option. On the other hand, consumers require acute drugs only when the need arises, compelling them to consume the first available option, instead of searching. Thus, consumers pay significantly less for chronic drugs.

What are the implications of the above argument in a context with liquidity shocks?

Let us develop a guiding hypothesis with the help of a theoretical argument.

**Choice of Drugs under Liquidity Constraints:** Under liquidity constraints, consumers will continue purchasing cheaper drugs if they fall within the budget set. In contrast, consumers will forego consumption of costlier acute drugs as they are less aware of cheaper alternatives. The following simple framework formalizes this argument. Assume that an agent suffers from two possible ailments $j \in 1, 2$. The prices for medicines of ailment $j$ is $p_j$ where $p_1 < p_2$. The utility from pain relief is $V$ and the agent's income is $M$.

The objective function of the patient is $Max\Sigma_j(V - p_j)$ subject to $\Sigma_j p_j \leq M$.

- **Case-1**: $\Sigma_j p_j \leq M$.
- **Case-2**: $p_j > M$.
- **Case-3**: $p_j \leq M$ for $j = \{1, 2\}$ but $\Sigma_j p_j > M$.

Under case 1, the liquidity constraint is not binding and the agent would consume both drugs. Under case 2, the agent can consume neither. Under case 3, only one medicine is affordable, compelling the agent to make a discrete choice. Agent incurs expense on $j = 1$ if $V - p_1 > V - p_2$; i.e. $p_2 > p_1$.

For the above argument to work, prices of chronic drugs should be lower than for acute drugs. What may drive this price differential? Sorensen (2000) reports that such a price difference may arise out of search behaviour. A vast literature exists on the impact of search on healthcare prices. Zhang *et al.* (2020) provides a review. Brown (2019); Prager (2020) and Lieber (2017) report substantial gains in healthcare savings from transparency and simplification of prices. Whaley (2019) finds that providers also respond strongly to online transparency by lowering costs for similar services.

We extend our framework to formalize Sorensen (2000)'s argument. Assume that the agent incurs a cost $c_j$ while *price-shopping*, which may include visiting pharmacies or bargaining for relationship discounts at the same pharmacy.[3] Let $p_j = h(c_j)$, where $h' < 0$ and $h'' > 0$; i.e. more search may allow discovery of cheaper alternatives but with decreasing returns. $h(.)$ reflects the efforts of patients in searching for lower prices (Lieber, 2017; Prager, 2020; Brown, 2019). The probability of recurrence of ailment $j$ is $q_j$, where $q_1 > q_2$. The expected utility for the agent from search for medicine of

[3] Chernew *et al.* (2018) finds evidence for price shopping by showing that insured patients tend to forego cheaper options for diagnostic tests.

ailment $j$ is $Max._{c_j} q_j(V - p_j) - c_j$ or $Max._{c_j} q_j(V - h(c_j)) - c_j$. We obtain $q_j h'(c_j) = -1$ or $h'(c_j) = \frac{-1}{q_j}$. Since $h'' > 0$, a higher $q_j$ implies a higher $c_j$; i.e. agents will exert more search costs for the ailment with higher recurring probability. Since $h' < 0$, a higher $c_j$ will imply a lower price for the medicine of higher probability ailment. Since chronic drugs have a probability 1 of recurrence, their prices will be lower.

Apart from the theoretical argument, what does our empirical data say about the price differential? We will discuss it in more details below —as a preview of the result, we do indeed find price indices of chronic drugs to be significantly lesser on an average than acute drugs once we account for the unobserved heteorogeneity at the level of regions, firms and drug supergroups.

# 3 Data and Summary Statistics

We use the All India Organization of Chemists and Druggists (AIOCD) database for our analysis, recently used in Adbi *et al.* (2022); Aggarwal *et al.* (2023). This database records the monthly sales volume and value of each Stock Keeping Unit (SKU) of medicines for 18 broad illness categories, known as supergroups, across 31 regions in India by 805 pharmaceutical companies.[4] We also observe other characteristics, such as whether the drug is used for chronic or acute conditions (drug type), whether it is to be consumed as a combination, and the weight of SKU. Our unit of observation is at the supergroup-drug type level; i.e. we use the monthly-level sales volume and value for all acute and chronic drugs in each of the 18 supergroups in 31 states of 805 companies. Sales volume is measured as the number of SKUs for each drug type. We compute the Price Index for this level as the weighted average of per milligram value of SKUs, where the weights are the share of sales volume in the supergroup-month-year-drug type level.

We use the observations from 2015, 2016 and 2017, which provide 22 months of pre-treatment and 14 months of post-treatment data. Table 1 provides the summary statistics. Average monthly sales for chronic drugs were 19624 SKUs before the income shock, which declined to 19238 in the post-shock period. Acute drug sales, however, declined by a bigger margin—from 17865 units in pre-shock to 16547 units in the post-shock period. Average monthly sales value for chronic and acute drugs were Rs. 1048950

[4]These illness categories or supergroups are Analgesics, Anti-Infectives, Anti-Neoplastics, Antidiabetics, Anti-malarials, Bloodrelated, Cardiac, Derma, Gastrointestinal, Gynaecological, Hormones, Neuro, Ophthal, Respiratory, Sextimulants, Urology, Vitamins and Others

and Rs. 753080.4 before demonetization. While the increase in average value of sales may reflect a secular inflationary trend, we will explore the differential outcomes for the acute and chronic drugs under liquidty shock.

Consistent with Sorensen (2000)'s results, the price dispersion of chronic drugs is lower. To check if the pre-conditions for our hypothesis are met, we use the pre-treatment data and regress the price index on an indicator which takes value 1 for acute drugs and 0 otherwise. We also include firm-, region- and supergroup-level fixed effects. Table 2 shows that within a firm, region and for a given illness category, the price of acute drugs is higher by Rs. 0.06 per mg before demonetization.

# 4 Motivating Empirical Illustrations

Before we move to our empirical methodology, we motivate our argument through some examples.

**Comparing a specific pair of drugs:** To build intuitions around the empirical patterns of sales, we consider two commonly sold drugs in India and the global south—Amoxycillin and Metformin. The former is an acute drug for infection outbreaks, while the latter treats diabetes, a chronic ailment. We run separate regressions of the log of sales of Amoxycillin and Metformin on state, month-year and pharmaceutical firm fixed effects. Figure 1 plots the coefficients for month-year effects from these regressions. The sales of Amoxycillin (blue circles) fall rapidly after demonetization (November 2016), whereas Metformin sales trend remain invariant. The results are nearly identical when we use the log of sales value as the dependent variable (figure 2).

**Comparing a specific pair of classes of drugs:** Next, we enlarge our example to consider the sales of all anti-infectives and all anti-diabetics to understand if the relationship holds for a broader set of drugs. Figure 3 plots month-year effects from a regression of the log of sales unit for all anti-infectives (blue circle) and anti-diabetics (red square). Other controls include state and firm fixed effects. Figure 4 repeats the results for the log of value of sales. The higher sensitivity of acute drugs relative to chronic drugs to demonetization remains robust even when we include all anti-infective medicines.

**Unconditional pro-cyclicality of acute sales share:** Finally, we check if the share of acute drug sales exhibits procyclicality —in particular, if unconditionally it comoves with the per capita GDP. Figure 5 plots three series. The thick black line

with the circular node is the annual GDP per capita growth rate from 2011 to 2019. De-trended shares of acute drug sales by volume and value are plotted as red triangles and blue squares, respectively[5]. The GDP growth rate is moderately positively correlated with these two series. The correlation coefficient with the share of sales by volume and value are 0.38 and 0.15, respectively. Therefore, acute drugs seem to possess positive correlations with per capita GDP growth rate. However, an unconditional estimate of correlation coefficient would not help us to pin down a causal effect. Therefore, in the next section, we design a difference-in-differences estimator to quantify the effect of an economic shock on the relative expenditures of acute versus chronic drugs.

# 5 Empirical Methodology

Identifying the impact of the income shock on planned and unanticipated expenditures is difficult. These two types of goods may have distinct time-invariant and time-varying unobservable characteristics affecting their expenditures. For example, demand for medical goods may vary by region and season due to climatic and socio-economic factors. Further, demonetization was an economy-wide shock which affected all regions and different economic actors. Unobservable supply-side factors and regional heterogeneity may also confound the illustration in the above case studies.

We address such challenges using the following difference-in-difference specification:

$$\log y_{dsrct} = \beta \times \text{Post}_t \times \text{Acute}_{ds} + \Phi_{st} + \Phi_{rt} + \Phi_{ct} + \epsilon_{dsrct} \tag{1}$$

$\log y_{dsrct}$ is the log of outcome variable for drug type $d$ (Acute or Chronic) in supergroup $s$ and region $r$, sold by company $c$ in month-year $t$. We use the total volume of sales (in units) and money value of sales as outcome variables. $\text{Post}_t$ is a time-varying indicator which takes the value 1 for months from November 2016 to December 2017, and 0 before that. $\text{Acute}_{ds}$ indicates the type of drug in supergroup $s$ by its usage. It takes a value of 1 for acute drugs and 0 for chronic. We include a rich set of fixed effects to control for time-varying unobservable confounders for supergroups , $\Phi_{st}$, region, $\Phi_{rt}$ and company, $\Phi_{ct}$. Our fixed effects account for the time-varying omitted variables across states, supergroups and companies which are affected by demonetization. This allows

[5]We de-trended the quarterly series using Hodrick-Prescott filter with a penalty/smoothing parameter of 1600.

us to identify the response of the income shock on consumption within regions, illness categories and companies.

A negative $\hat{\beta}$ would indicate a contraction in volume and value of sales. Two reasons may drive this contraction. First, households reduce expenditure on acute drug sales, consistent with our theoretical arguments. Second, firms may also reduce their supply or production of drugs as they face operational challenges due to lack of cash.

**Supply Contraction**: A supply-side contraction is more likely to occur for domestic firms as they tend to be more informal and cash-reliant. To assess if the contraction was supply driven, we use the following extension of equation 1:

$$\log y_{dsrct} = \beta \times \text{Post}_t \times \text{Acute}_{ds} + \gamma \times \text{Post}_t \times \text{Acute}_{ds} \times \text{Domestic}_c + \Phi_{st} + \Phi_{rt} + \Phi_{ct} + \epsilon_{dsrct} \quad (2)$$

where, $\text{Domestic}_c$ takes the value 1 for domestic companies and 0 for MNCs. The remaining variables are as defined for equation 1. A negative value for $\gamma$ would indicate the domestic firms experienced a larger decline in sales consistent with supply-side disruption due to lack of cash.

**Demand Contraction**: Under a demand-driven contraction, the poorer states should experience a larger decline in sales, as liquidity constraints would be more binding for the households in these states. We test this argument using the following specification:

$$\log y_{dsrct} = \beta \times \text{Post}_t \times \text{Acute}_{ds} + \theta \times \text{Post}_t \times \text{Acute}_{ds} \times \text{LowIncome}_r + \Phi_{st} + \Phi_{rt} + \Phi_{ct} + \epsilon_{dsrct} \quad (3)$$

where, $\text{LowIncome}_r$ takes value 1 for poorer states.[6]. A negative $\theta$ will indicate a larger sales decline in states where the liquidity constraint is more binding.

A final threat to identification may occur due to diverging pre-trends in the consumer expenditure trends across these drugs. However, it is extremely unlikely that consumer expenditure changed in anticipation of the income shock we exploit in this paper, as it was an entirely unexpected event.[7] Nevertheless, we check for parallel pre-trends to rule out any bias due to diverging trends in consumption behaviour across the acute and

[6]These states are Bihar, Chattisgarh, Jharkhand, Madhya Pradesh, Rajasthan, Odissa, Uttar Pradesh, West Bengal and all the North-Eastern states.

[7]This was part of the design of the demonetization announcement that there would be no prior knowledge around it. The Indian economy was suffering from counterfeit currencies and one of the major goals of demonetization was to make fake currencies become useless. Hence, it necessitated a lack of information about the impending announcement about demonetization so that the counterfeit currencies could not be exchanged for legal currencies. See for example: "Notes out of circulation". The Times of India, 8th November 2016.

chronic drugs.

# 6 Results

In this section, we provide the empirical results along with mechanisms and robustness checks.

## 6.1 Expenditures on Acute vs. Chronic Drugs

The first result is on how the expenditure on acute drugs change with respect to chronic drugs. Table 3 presents the estimation results of equation 1. In column 1, we use the log of total volume of sales as the outcome variable. The coefficient is -0.045 with a standard error of 0.009. Thus, compared to chronic drugs, total volume of acute drugs declined by 0.045 log points or nearly 4.6% due to the income shock. Column 2 provides the results for log money value of sales. Here, as well, we find money value of acute drug sales to decline by nearly 2.7% after demonetization, compared to the expenditure on chronic drugs.

Therefore, expenditure on acute drugs fall relative to chronic drugs post-demonetization. The fall in volume shows that the effect is also seen in quantity, and not only by changes in prices. This leads us to the question —do the prices react? After all, expenditure may change due to changes in prices as well. We note here that a priori, the likelihood of finding a change in prices is small. This is because of two reasons. One, drug prices in India are regulated by the government. This creates stickiness in prices directly (see Chatterjee *et al.* (2015, 2019)). Two, demonetization was understood to be a transitory phenomenon which would disallow firms to consider this as a permanent shock. Later empirical research also found that the effect was temporary (Chodorow-Reich *et al.*, 2020). Thus, it is quite unlikely that firms would be willing to alter prices due to an unanticipated and short-lived shock.

We test this explicitly in our data. In column 3, we use the price index as the dependent variable and regress it according to equation 1. The coefficient on the interaction term is -0.003 with a standard error of 0.012. This shows two points. One, clearly prices did not change in a statistically significant manner. Two, we can safely conclude that expenditure decline was not likely due to a drop in prices, and we can attribute it to a decline in quantity (which we describe as 'sales volume'). Thus the liquidity shocks had

a real effect —not nominal.

## 6.2 Mechanisms—Demand and Supply-side Factors

Our discussion so far shows that there was a decline in volume and value of acute drug sales after a negative liquidity shock. Let us focus on the quantity decline as that is the primary driver of the decline in sales value.

What caused the decline in quantity? There are two channels —demand-side of the economy and supply-side of the economy. To elaborate, this decline can occur due to a demand contraction, where households restrict expenditure on acute drugs relative to chronic drugs. But at the same time, we note that the supply-side may also be responsible. Demonetization affected both the consumers and the producers. In particular, firms were also directly impacted (Lahiri, 2020). For example, a large fraction of firms in India were cash-reliant. The production and supply chain depended on the availability of cash. Therefore, an unexpected cash shortage may directly affect the firms.

Simply looking at the quantity decline would not allow us to answer this question —Was the differential impact of demonetization on acute drug sales then demand contraction or supply contraction? We unpack our results across these two dimensions.

### 6.2.1 Supply Contraction

Multinational firms are usually more productive and have better contractual arrangements. They are also less likely to transact in cash with their distributors and suppliers. This makes them less vulnerable to cash constraints than their domestic counterparts. If the decline in sales was entirely a supply response of cash-reliant firms, then the sales of multinational-owned drugs are less likely to be affected. We use the specification in equation 2 to test this hypothesis.

Table 4 provides the results. The coefficient on the triple interaction term, $\gamma$, is positive—domestic firms suffer lower shocks than foreign firms. Notably, the coefficient on the difference-in-difference term is -0.314 for log volume and -0.307 for log value. Combining the above estimates we see that the multi-nationals suffer a contraction of nearly 30%, whereas the contraction for domestic firms is around 2-3%. Thus domestic firms were less affected than multinationals which are less cash-reliant. This rules out supply response as the major factor behind the decline in quantity.

### 6.2.2 Demand Contraction

Under a demand contraction, poorer states, which are more reliant on cash and have less developed credit markets, are more likely to suffer a larger negative shock after demonetization. As a consequence, the magnitude of acute drug contraction should be higher in these states. We explore this hypothesis using the specification in equation 3.

Table 5 presents the results for volume and value of acute drugs sold relative to chronic drugs in columns 1 and 2, respectively. The difference in differences coefficient remains significantly negative in both specifications. Importantly, the coefficients on the triple interaction terms are significantly negative; i.e. the decline in salesunits and sales volume on acute drugs vis-à-vis chronic drugs was 2.4% and 3.1% more in low-income states relative to high-income states. This is consistent with the demand contraction hypothesis described right above.

We summarize the findings so far before providing additional evidence. We saw that the sales decline of acute drugs relative to chronic drugs is primarily driven by the quantity channel and not the price channel. Exploring closely, we found marginally significant support for the demand side factors than the supply withdrawals.

So far, we have used the distinction of chronic and acute drugs in our analysis. But, these categories span multiple illnesses. Does consumers' response vary with the urgency of the treatment? We next explore the heterogeneity across illnesses.

## 6.3 Heterogeneity across Illness Sub-categories

So far we have classified all drugs as either belonging to acute or chronic diseases. The categorization is useful for our purpose of tracking anticipated and relatively less anticipated—or completed unanticipated—expenditures. However, we note that acute conditions may occur in a large class of illnesses. Further, wide variation exists on the need of acute drugs depending on the nature of the illness. We focus on acute drugs here since that is where there is substantial heterogeneity in terms of the urgency of the expenses. Some acute ailments, such as cardiac attack or appendicitis, are nearly impossible to delay. On the other hand, patients may revert to household remedies for some minor acute illnesses such as gastro-intestinal issues. For which kind of illnesses, does the contraction in acute drug intake occur? This will further reveal consumers' choices under liquidity shocks, and may also indicate potential welfare loss.

We use the AIOCD classifications for defining and analyzing the sales behaviour

across various illnesses. We construct samples for four commonly occurring ailments in India separately—Gastrointestinal, Anti-malarial, Respiratory and Cardiac.[8] We regress the log of sales volume for acute medicines for these four categories on month-year, state and firm-level fixed effects. Figure 6 plots the month-year effects from these four regressions.

Interestingly, anti-malarial acute drugs (yellow diamonds) exhibit the steepest fall after demonetization, whereas cardiac drug sales (blue circles) remain invariant throughout. This pattern is quite intuitive. Cardiac drugs cannot be delayed and constitute some of the most urgently required treatments. The other three, especially, gastrointestinal and anti-malarial drugs can be potentially delayed in terms of consumption (relative to cardiac illnesses). In summary, within-acute variation in elasticity of consumption arising out of urgency of health situation may amplify or mitigate the effect of liquidity shock.

Given the nature of the illnesses, there can be an effect of seasonality. Especially, tropical diseases like malaria tend to flare up during the monsoon seasons. So one could possibly consider the decline in the drug purchase for malaria to be attributed to seasonal variations. But, we note that the suppression of sales after demonetization is higher than the corresponding levels for the months across a full year before demonetization. Thus, these findings are largely consistent with our original hypothesis that consumers delay consumption of goods which can be avoided in times of liquidity shocks.

## 6.4 Robustness Checks

In this section, we provide additional tests to assess the robustness of our results.

### 6.4.1 Parallel Pre-Trends

While our empirical methodology addresses several time-varying unobservable confounders at the state, company and supergroup level, diverging trends in the planned and unanticipated expenditures in the absence of the income shock would bias our results. Such a counterfactual is difficult to observe but could occur due to several reasons. The demonetization shock coincided with the winter season in India, when demand for certain chronic drugs, such as bronchodilators used for respiratory ailments and diseases, spikes due to lower temperatures and increased pollution. Another possibility could be that households altered their behaviour in anticipation of the income shock, though the

[8] AIOCD classifies medicines into 18 broad illness categories.

likelihood of such an anticipation is remote, as argued in the literature on demonetization (Karmakar & Narayanan, 2020; Chodorow-Reich *et al.*, 2020; Wadhwa, 2020).[9]

To account for these concerns, we use the trends between the sales of these drugs before the shock as a proxy for parallel trends in the counterfactual scenario. Our pre-treatment period spans 22 months, allowing us to control for seasonal drug demand fluctuations. We use the following specification:

$$\log y_{dsrct} = \gamma_t \times \text{Month-Year}_t \times \text{Acute}_{ds} + \Phi_{st} + \Phi_{rt} + \Phi_{ct} + \epsilon_{dsrct} \tag{4}$$

where, $\text{Month-Year}_t$ is a dummy variable for each month-year. Other variables are as described above. We normalize the $\gamma_t$ value to zero for October 2016, the first month before the income shock. Thus, each coefficient represents the difference in acute and chronic drugs in each month with respect to the difference in October

Figures 8 and 7 plots the coefficient $\gamma_t$ against each month-year. For each of the outcome variables, none of the pre-treatment coefficients is significantly different from zero, ruling out any pre-treatment trend differences. Further, we see a declining trend after the income shock. Figure 9 conducts the corresponding analysis for prices. Here, we find that the trends remain unchanged from pre- to post-treatment periods.

### 6.4.2 Assessment using a Matched Control Group

Our specification controls for several time-varying factors at the state, company and illness category level. However, chronic and acute drugs can be distinct across unobservable factors, which can influence expenditure on these items. Although testing for parallel pre-trends serves as a proxy to address time-varying unobservable factors, we further assess the robustness of our results by restricting the analysis to a subset of control group observations matched with the treated group on several variables. Smith & Todd (2005) finds that such an estimator can address temporally-invariant bias. Further, if the bias from the time-varying and time-invariant unobservables is proportional, then such an estimator can address time-varying factors as well (Altonji *et al.*, 2005) We include the number of SKUs, share of Indian firms, Inter-Quartile range of average value, whether the drug is to be used in a combination or not, and fixed effects for supergroups, companies and states, as covariates for matching.

[9]For the lack of anticipation, see for example: "Notes out of circulation". The Times of India, 8th November 2016.

While several matching algorithms exist, we assess the robustness of our results by using coarsened exact matching (Iacus *et al.*, 2012). In CEM, observations are matched within coarse partitions of the covariates. Table 6 provides the results. Our results remain similar to the results in table 3. The effect of the income shock is significantly negative for volume (column 1) and value of drug sales (column 2).

### 6.4.3 Randomization Inference

As a final robustness test, we conduct randomization inference (Barrios *et al.*, 2012; Ding *et al.*, 2016). Under this process, the treatment indicator is randomly assigned observations to generate a pseudo-distribution of treatment. The treatment effect, or the coefficient on the interaction term, is estimated with the new pseudo-distribution. If the true treatment has a significant effect on drug sales, then the pseudo-treatment effect will be distinct from the original estimate. Conversely, if the pseudo-treatment effect is statistically similar to the original estimate, then we conclude an absence of the treatment.

Randomization inference has several advantages for our context. First, in our study, each illness group has both acute as well as chronic drugs. Thus, the treatment varies by individual observations and not groups or clusters, which disallows adjusting standard errors for within-group heteroscedasticity. Conley & Taber (2011) and MacKinnon & Webb (2020) note that randomization inference can be useful for difference-in-difference studies with few clusters. This method also serves as a placebo check by generating alternative pseud-estimates (Hagemann, 2019). As with conventional placebo tests, if the pseudo-estimate is distinct from the original estimate, we reject the null hypothesis of no treatment effect. Finally, this process is also useful when the treatment effect is not randomly assigned.

We repeat this process 50 times to generate a distribution of pseudo-treatments, denoted by $\hat{\beta}_\tau$, where $\tau \in \{1, 2, ...50\}$. The null hypothesis of no treatment effect is $\hat{\beta}^* - \hat{\beta}_\tau = 0$, where $\hat{\beta}^*$ is the original estimate. We conduct a t-test to check the null hypothesis.

Figures 11 and 10 plot the distributions of estimates obtained from 50 randomization inferences with log of value and log of volume as outcome variables, respectively. In either case, we find the original estimate is significantly outside the distribution. Thus, we strongly reject the null hypothesis of no treatment effect under the observed treatment assignment.

# 7 Summary and Conclusion

How does healthcare expenditure respond to economic shocks? The answer to this question will likely depend on the institutional context, specifically, whether insurance markets exist or not to partially absorb the shock (Jeske & Kitao, 2009). The endogeneity problem between healthcare expenditure and economic variables is pervasive due to both-way causality. The literature attempts to disentangle the effect in various ways. The effect of health shock on economic outcomes can be causally identified using econometric estimations exploiting sudden exogenous health shocks. A similarly exogenous channel in the reverse direction is difficult to come up with. Typically, the literature has relied on more coarse-grained regional income shocks, possibly instrumented, to explore the effects on healthcare expenditure and health, more broadly.

We exploit a sudden, well-identified economic shock of demonetization in India which left 86% of the existing cash useless overnight. This episode is associated with a temporary economic dip (Chodorow-Reich *et al.*, 2020). We exploit this event to design a quasi-natural experiment to see how the sales of medicines for acute illness, which are unplanned consumption, responded compared to the sales of medicines for chronic illnesses which are planned consumption.

The sales of medicines for acute illness showed a contemporaneous fall relative to medicines for chronic illnesses. This causally identified scenario implying procyclicality in unplanned expenditure relative to planned expenditure, is consistent with the longer-term time series data. We also find that the effects might be driven by demand side factors more than supply side factors and survive several robustness checks.

Our work adds to the literature developed by Ruhm (Ruhm, 2000, 2015, 2016). One novel addition of our work is to bring forth granular product-region-time level data in this literature as opposed to region-time level data (e.g. Ruhm (2000)) or household-time (e.g. Monheit *et al.* (2020)) level data. Our work also provides a plausible channel through which healthcare expenditure may react to liquidity provisions, and connects healthcare to macroeconomic variables. Thus our work provides a more causal interpretation beyond Ruhm's work.

We end the paper with an observation. Our data allows us to disentangle the effects at the level drug sales—or conversely expenditure by households on consuming these drugs. We have not explored the effects on consumer welfare due to the lack of availability of household-level consumption or health outcomes data. Therefore, our ability to describe

the welfare implications is limited in the present context. Future research can shed more light on the question of welfare.

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# 8 Figures

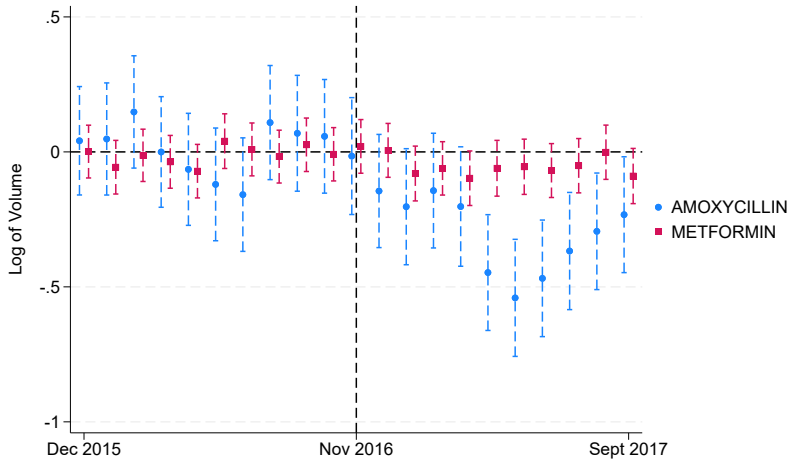


Figure 1: Trends in volume of sales for Amoxycillin (acute) and Metformin (chronic). The fall in volume of Amoxycillin post-demonetization (the dashed vertical line in November 2016) is evident. Metmorfin sales volume remains stable.

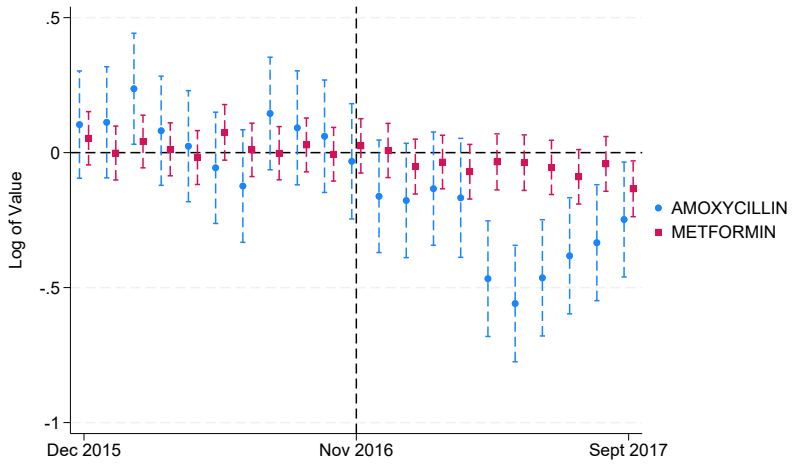


Figure 2: Trends in value of sales for Amoxycillin (acute) and Metformin (chronic). The fall in value of Amoxycillin post-demonetization (the dashed vertical line in November 2016) is evident. Metmorfin sales value remains stable.

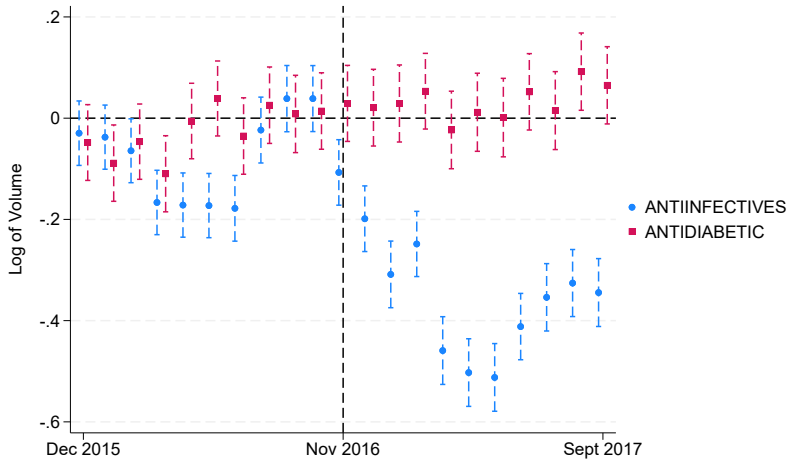


Figure 3: Trends in volume of sales for anti-infective (acute) and anti-diabetic (chronic) drugs. The fall in volume of anti-infective drugs post-demonetization (the dashed vertical line in November 2016) is evident. Anti-Diabetic drugs' sales volume remains stable.

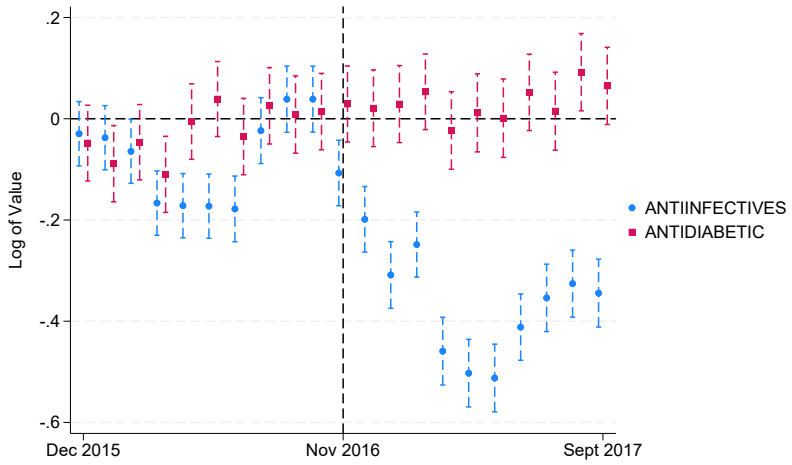


Figure 4: Trends in value of sales for anti-infective (acute) and anti-diabetic (chronic) drugs. The fall in value of anti-infective drugs post-demonetization (the dashed vertical line in November 2016) is evident. Anti-Diabetic drugs' sales volume remains stable.

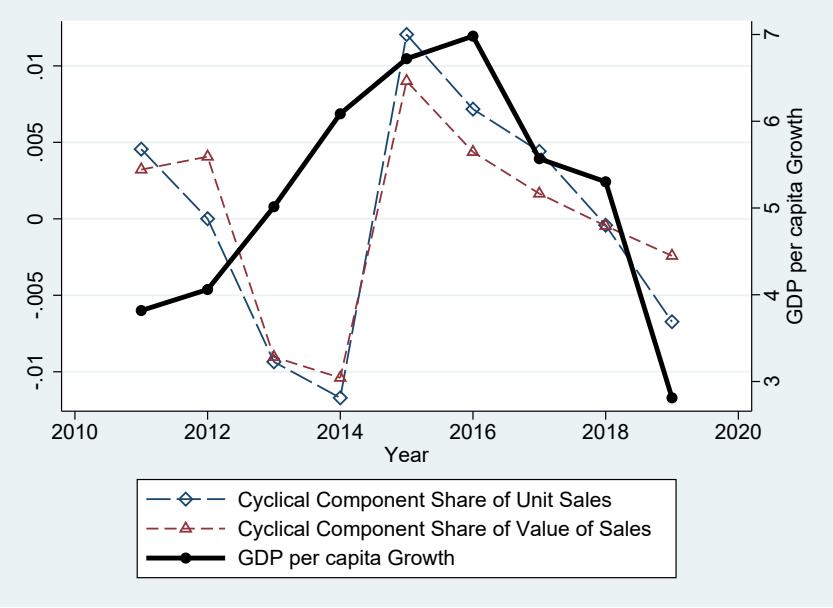


Figure 5: Quarterly share of acute drugs sales out of total drug sales and growth rate of GDP per capita in percentage. Correlation coefficient between growth rate of GDP per capita and cyclical components of Share of unit sales and share of sales value are 0.38 and 0.15, respectively.

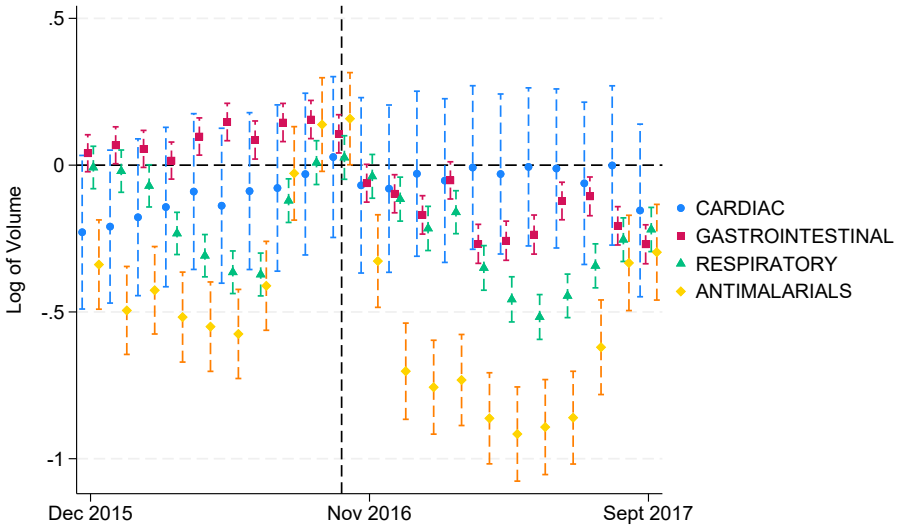


Figure 6: Trends in the sales volume of acute drugs for cardiac, respiratory, gastrointestinal and anti-malarial drugs. The fall in anti-malarial drugs sales volume is quite evident. Gastrointestinal and respiratory drug sales decline post-demonetization, but to a much lesser extent than anti-malarial drugs. Cardiac drug sales volume does not respond significantly and remains stable.

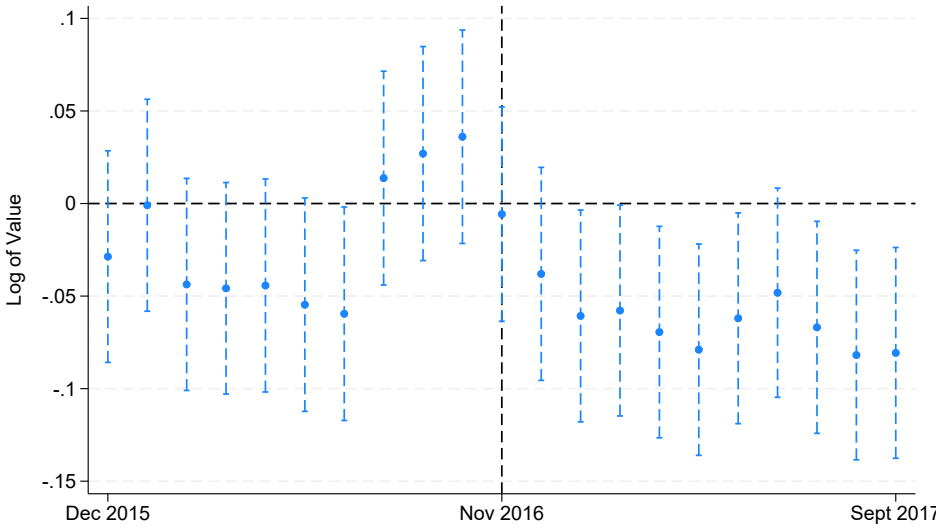


Figure 7: Assessing parallel pre-trends in acute and chronic drug sales value. The decline in the acute sales volume vis-à-vis chronic sales value post-deomonitization is evident.

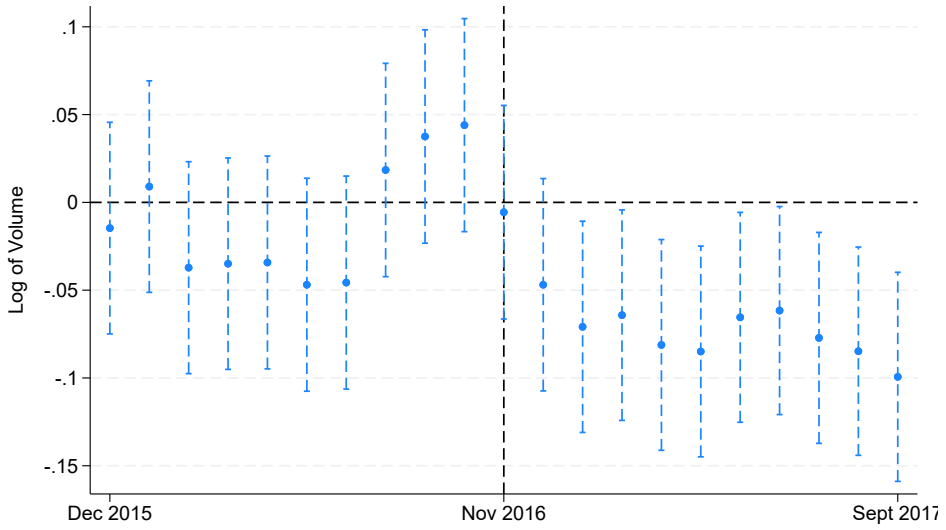


Figure 8: Assessing parallel pre-trends in acute and chronic drug sales volume. The decline in the acute sales volume vis-à-vis chronic sales volume post-deomonitization is evident.

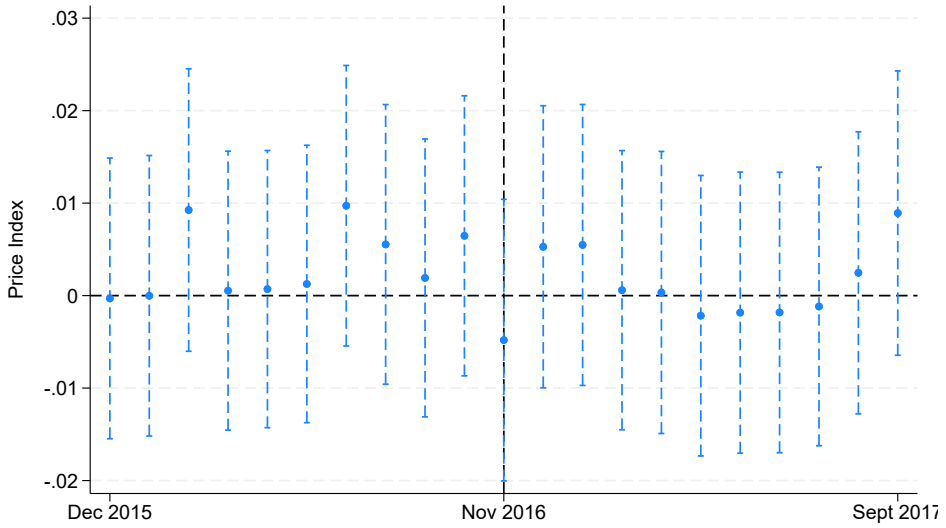


Figure 9: Assessing parallel pre-trends in acute and chronic drug prices. Prices show stickiness and post-demonetization there is no signs of price adjustments.

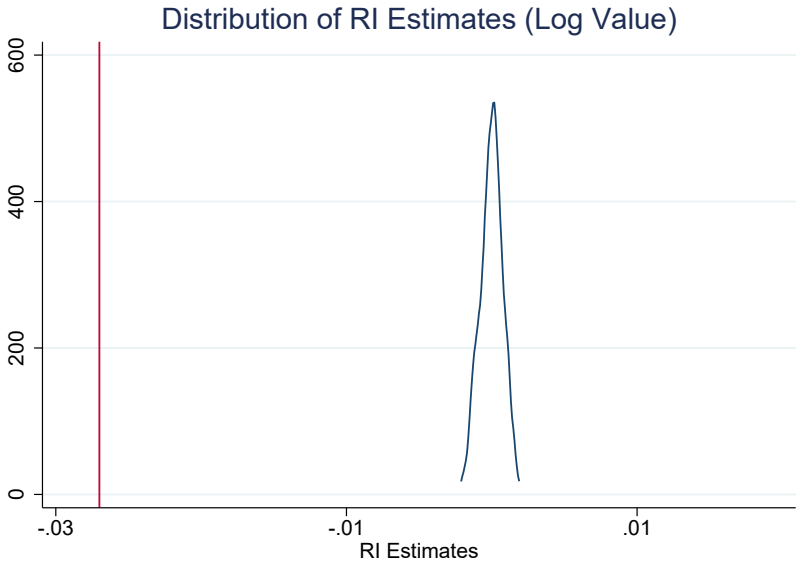


Figure 10: Distribution of estimates for log value under randomized inference test. The red vertical line shows the estimated value which lies far beyond the distribution of the coefficients obtained via randomized inference test. Therefore, the estimated coefficient for log value is statistically significant.

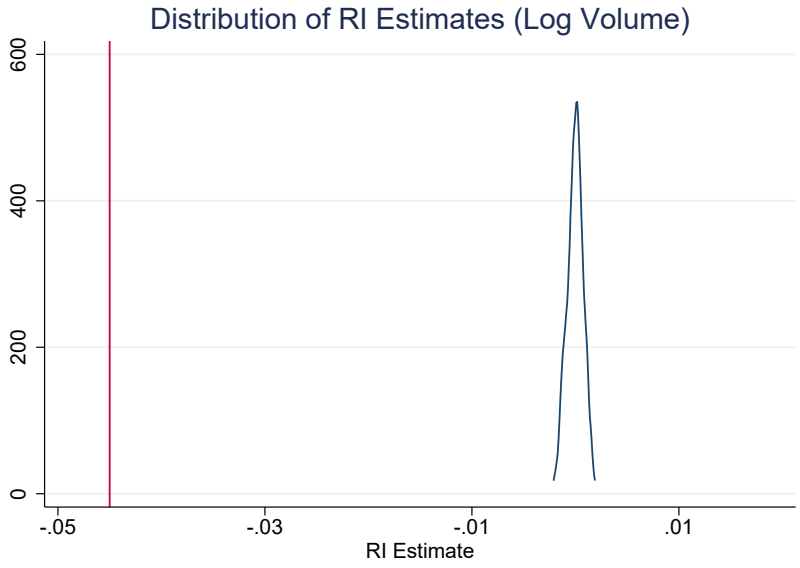


Figure 11: Distribution of estimates for log volume under randomized inference test. The red vertical line shows the estimated value which lies far beyond the distribution of the coefficients obtained via randomized inference test. Therefore, the estimated coefficient for log volume is statistically significant.

# 9 Tables

Table 1: Summary Statistics on Acute and Chronic Drugs

| | Pre-Treatment | | Post-Treatment | |
|---|---|---|---|---|
| | Chronic | Acute | Chronic | Acute |
| Sales Volume | 19624.65 | 17865.12 | 19238.36 | 16547.74 |
| | (85281.47) | (87574.91) | (85760.64) | (83337.19) |
| Sales Value (INR) | 1048950 | 753080.4 | 1138287 | 753253.7 |
| | (4141117) | (4570945) | (4702823) | (4201157) |
| Price Index | .188 | .144 | .186 | .141 |
| | (.707 ) | (.701) | (.708 ) | (.698) |
| IQR* | 51.63 | 81.37 | 58.49 | 90.71 |
| | (417.53) | (1232.82) | (484.58) | (1180.91) |
| Number of SKUs | 1102777 | 929824.6 | 1208200 | 1011687 |
| | (1207722 ) | (910745.4) | (1267348) | (956768.8) |
| Observations | 548,595 | 578,615 | 369,966 | 394,039 |

**Notes:** Price Index is computed as a weighted average of per mg value of SKU, where the weights are the share of the SKU in total sales. *Inter-Quartile Range.

Table 2: Pre-Demonetization Prices Differential between Acute and Chronic Drugs

| | Price Index |
|---|---|
| Acute | 0.0606*** |
| | (0.0136) |
| Obs. | 1,745,590 |

**Notes:** Coefficient from a regression of price index on an indicator for acute drugs. The observations are restricted to pre-Demonetization data (January 2015-November 2016). Region, firm and supergroup-level FEs are included.

Table 3: Income Shock and Consumption Response on Acute Drugs

| | Log(Volume) | Log(Value) | Price Index |
|---|---|---|---|
| interaction | -0.045*** | -0.027*** | -0.003 |
| | (0.009) | (0.008) | (0.012) |
| Observations | 1889890 | 1889835 | 1889835 |
| $R^2$ | 0.438 | 0.467 | 0.188 |
| Adjusted $R^2$ | 0.430 | 0.459 | 0.176 |

**Notes:** Columns 1, 2 and 3 report the coefficient on the interaction term from a regression of log of total quantity, log of money value and price index of drugs on the difference-in-difference indicator. Each regression controls for state-month, company-month and supergroup-month fixed effects. The dependent variable is winsorized from the right tail at 1% level. */**/*** denote significance at 10/5/1 percent level. Following Abadie *et al.* (2023), standard errors are robust to heteroscedasticity at the broad illness category of the medicines.

Table 4: Income Shock and Consumption Response on Acute Drugs across Foreign and Domestic Firms

| | Log(Volume) | Log(Value) |
|---|---|---|
| interaction | -0.314*** | -0.307*** |
| | (0.028) | (0.026) |
| interaction_indian | 0.290*** | 0.296*** |
| | (0.028) | (0.026) |
| Observations | 1889890 | 1889835 |
| $R^2$ | 0.438 | 0.467 |
| Adjusted $R^2$ | 0.430 | 0.460 |

**Notes:** Column 1 (2) reports the coefficient on the interaction term from a regression of log of total quantity (money value) of drugs on the difference-in-difference indicator and the interaction between the difference-in-difference indicator and a dummy for domestic firms. Each regression controls for state-month, company-month and supergroup-month fixed effects. The dependent variable is winsorized at 1% level. */**/*** denote significance at 10/5/1 percent level. Following Abadie *et al.* (2023), standard errors are robust to heteroscedasticity at the broad illness category of the medicines.

Table 5: Income Shock and Consumption Response on Acute Drugs across Rich and Poor States

| | Log(Volume) | Log(Value) |
|---|---|---|
| interaction | -0.037*** | -0.017* |
| | (0.010) | (0.010) |
| interaction_lowincome | -0.024* | -0.031** |
| | (0.013) | (0.013) |
| Observations | 1889890 | 1889835 |
| $R^2$ | 0.439 | 0.467 |
| Adjusted $R^2$ | 0.430 | 0.460 |

**Notes:** Column 1 (2) reports the coefficient on the interaction term from a regression of log of total quantity (money value) of drugs on the difference-in-difference indicator and the interaction between the difference-in-difference indicator and a dummy for low income states. Each regression controls for state-month, company-month and supergroup-month fixed effects. The dependent variable is winsorized from the right tail at 1% level. */**/*** denote significance at 10/5/1 percent level. Following Abadie *et al.* (2023), standard errors are robust to heteroscedasticity at the broad illness category of the medicines.

Table 6: Assessment using a Matched Control Group—Coarsened Exact Matching

| | Log(Volume) | Log(Value) |
|---|---|---|
| interaction | -0.038*** | -0.025*** |
| | (0.009) | (0.008) |
| | (0.005) | (0.005) |
| Observations | 1713745 | 1713690 |
| $R^2$ | 0.429 | 0.459 |
| Adjusted $R^2$ | 0.420 | 0.451 |

**Notes:** Column 1 (2) reports the coefficient on the interaction term from a regression of log of total quantity (money value) of drugs on the difference-in-difference indicator. The control group (chronic) is matched with the treatment group using coarsened exact matching. Each regression controls for state-month, company-month and supergroup-month fixed effects. */**/*** denote significance at 10/5/1 percent level. Following Abadie *et al.* (2023), standard errors are robust to heteroscedasticity at the broad illness category of the medicines.