**Paper Title:**
Government policy, strategic consumer behavior, and spillovers to retailers: The case of demonetization in India

**Submitting Author Information:**
Author's First Name: Yewon
Author's Last Name: Kim
Author's Affiliation: Stanford Graduate School of Business
Author's Title: Assistant Professor of Marketing
Author's Email Address: yewonkim@stanford.edu
Author's Mailing Address: 655 Knight Way, Stanford, CA 94305
Author's Phone Number: 312-256-7675

**Identify Paper Category:**
Empirical

**Co-Author(s) Information:**
**Co-Author 1:**
First Name: Pradeep
Last Name: Chintagunta
Email Address: pradeep.chintagunta@chicagobooth.edu

**Co-Author 2:**
First Name: Bhuvanesh
Last Name: Pareek
Email Address: bhuvanesh.pareek@iimb.ac.in

# Government policy, strategic consumer behavior, and spillovers to retailers: The case of demonetization in India

Yewon Kim* Pradeep Chintagunta† Bhuvanesh Pareek‡

October 2021

**Abstract**

This paper studies strategic consumer shopping behavior in response to a macroeconomic policy and quantifies its unintended consequences for retailers vis-à-vis the policy goal. Using transaction-level data from a large retail chain in India, we document consumer strategies that leverage retailers to avoid costs associated with the country's currency reform policy. We observe both an increase in returns of cash-purchased items that were bought before demonetization (*strategic returns*) and a spike in final (unreturned) cash purchases with soon-to-be-illegal notes (*strategic purchases*). Both practices serve consumer incentives either to receive legal notes from the retailer or to avoid depositing cash in formal bank accounts. Our analysis suggests that strategic consumers benefited the retail chain while hindering the intended policy effect, leaving 20 million INR ($0.3 million) of demonetized notes outside the formal tax network through this retail chain only; when we scale up the estimates to the country's market size, the estimated total impact reaches 100 billion INR ($1.5 billion). Our findings offer implications for policy makers by quantifying a wide spillover effect of government interventions that goes beyond the target group, and document a new role of the retail industry - of absorbing, and facilitating a response to, macro shocks.

*keywords:* Strategic consumer behavior, Unintended consequences, Product returns, Public policy, Policy evaluation, Currency reform.

*Stanford Graduate School of Business, yewonkim@stanford.edu
†University of Chicago Booth School of Business, pradeep.chintagunta@chicagobooth.edu
‡Indian Institute of Management, Indore, bhuvaneshp@iimidr.ac.in

We thank several executives from an anonymous retail chain for the main dataset; Prachi Mishra, Raghuram Rajan and Nagpurnanand Prabhala for their help in accessing supplemental data used in the study; Wes Hartmann, Navdeep Sahni, Anita Rao, Yanwen Wang, Sridhar Narayanan, Harikesh Nair, James Lattin, and participants at Stanford and Chicago Booth marketing seminars for their helpful feedback. Chintagunta thanks the Kilts Center of Marketing at the University of Chicago for financial support

# 1 Introduction

We study strategic consumer shopping behavior in response to a macroeconomic policy - currency reform - and quantify its unintended consequences for retailers as well as for the policy goal. Understanding how macroeconomic policies affect consumer and firm behaviors has been an ongoing endeavor in various streams of research. (E. Anderson & Simester (2008), Dubé et al. (2018), Biswas et al. (2019) [business cycles]; Maggio et al. (2017) [interest rates]; Reece & Zieschang (1985) [tax deduction]; Adjerid et al. (2016), Lin (2019), Aridor et al. (2020) [privacy regulations]; E. Anderson et al. (2010), Bollinger & Sexton (2017), Seiler et al. (2020) [sales tax]; Bollinger et al. (2011), Rao & Wang (2017) [food labeling]; M. C. Cohen et al. (2016), Xiao et al. (2020), He et al. (2021) [subsidy]). The topic has stayed important and relevant for several reasons. First, with the changing market landscape, new macroeconomic interventions are constantly being introduced. Second, the ever-connected and complicated nature of the market creates large unanticipated spillovers outside the policy target (Fletcher et al. (2010), Kostov & Schechner (2019)). Although "much more detailed review must be given to the range of potential unintended consequences" of macroeconomic interventions (Hall (2014)), existing research devotes most of its efforts on documenting outcomes *within* the policy target. If a policy creates a significant spillover that reaches far beyond the target sector, casting a wider net outside the intended subjects of policies would be critical at assessing the net policy impact not only for policy makers but also for other potentially affected market sectors.

Using micro-level data from a retail chain, we document wide spillovers of a macroeconomic intervention to agents outside the policy's target group. Specifically, we report an unintended, economically significant increase in a retailer's revenue due to a currency reform policy, which arises from strategic consumers' shopping activities. Our empirical context is the demonetization policy in India. On November 8, 2016, the Government of India announced demonetization of all

500 and 1,000 INR banknotes and issuance of new 500 and 2,000 INR banknotes, effective as of the next day. To exchange the banned notes for new ones, people had to either exchange them at banks (but subject to a low daily limit) or deposit them into their bank accounts. Since the government was concerned that some citizens were holding cash outside the tax system, one of the key objectives of this previously unannounced policy was to curb such holdings and to bring unaccounted money into the formal tax network (A. Lahiri (2020)). However, statistics and research findings suggest that it is ambiguous whether the policy achieved its intended goal; although there was no significant short-term increase in the number of tax payers or direct tax revenues due to the policy (A. Lahiri (2020)), the Reserve Bank of India reports that 98.8 percent of the old currency notes were returned into the Indian banking system in about 6 months after the announcement of demonetization. This raises the question of whether the policy effectively cleared unaccounted money and addressed related tax issues.[1]

Media reports suggest that people's strategic behavior to circumvent the policy might have played a significant role in thwarting the government's intentions. According to these reports, to retain the value of their cash without depositing it into the banking system, many people used banned bills to buy high-priced items the night before the policy became effective (after policy announcement) or even asked for backdated receipts after the policy went into effect.[2] If these consumer actions had a sizeable economic impact, it is important for both retailers and policy makers to understand consumer incentives and possible consumer actions in response to the policy or to any macro-level interventions with similar aims.

Using transaction-level data on non-perishable, high-ticket item purchases from a large retail chain in India, we observe strategic consumer behavior in response to the currency reform policy.[3]

[1] "Has Demonetization Achieved its Stated Objectives?", Madhyam, September 13, 2017.

[2] "Indians Rush Frantically to Launder Their 'Black Money,'" The New York Times, November 20, 2016.

[3] We do not reveal the product category following the agreement with the data provider. Here, big ticket items refer to non-perishable products with high average ticket prices. Examples include jewelry, consumer electronics, large appliances, and high-end saris and apparel, and we do not identify which product category our data provider

The abruptness of the policy, combined with the size of the retail chain, allows us to safely assume that there was no immediate strategic responses from the supplier side overnight, including changes in prices and return policies.[4]

First, we observe *strategic returns*, which are characterized by an increase in returns of the sales that are made in old cash notes prior to demonetization. Such returns gave consumers their cash back in legal bills that do not have to be exchanged or deposited at the banks. Therefore, an increase in returns is consistent with people's efforts to secure legal notes without waiting in line at the banks or without putting cash into taxable bank accounts.

Second, *strategic purchases* are observed, which are identified as a spike in *unreturned* purchases with soon-to-be-illegal cash notes on the day of announcement (i.e., one day before the effective date of demonetization). Throughout this paper, we use unreturned purchases and *final* purchases interchangeably to refer to the purchases that are not returned. We further decompose these strategic purchases into three actions with different incentives: switching of payment methods, accelerated purchases, and incremental purchases.

Switching to cash from other payment options, identified as reduction of non-cash transactions on the day of announcement, occurs as consumers choose to pay with soon-to-be demonetized notes to save the cost of exchanging them at the banks. Accelerated purchases, identified as the amount of dip in total sales after the policy implementation, take place on the day of announcement as consumers expedite their planned purchases to spend old notes and save on exchange costs. For households that plan future purchases, demonetization can be viewed as making the old notes "cheaper" than their face value given the costs people have to incur to exchange them to the new notes. Therefore, the net price paid in the old notes on the day of announcement is lower than the same value paid in the new notes, which is equivalent to a price promotion on the day of

sells.

[4]Small-scale independent businesses may have had more flexibility with store policies than a large retail chain had.

announcement until the policy becomes active the next day. Incremental purchases are obtained as excess final sales in cash on the day of announcement on top of switching to cash and accelerated purchases. Incremental purchases, unlike the first two types of purchases, align with the incentive to avoid depositing cash to taxable bank accounts. With a model, we illustrate how different underlying incentives can result in the observed aggregate increases in returns and cash sales.

Our analysis shows that different types of strategic consumer behavior overall benefited the retail chain while partly hindering the intended effect of the currency reform policy. Households could save on tax payments or related penalties by making strategic purchases with soon-to-be-demonetized notes instead of depositing them in their bank accounts, which had a positive impact on store revenues. Households could even potentially recoup some of the cash value by reselling the purchased durable goods in the informal economy, given that the second hand market in India is estimated to be over 600 billion INR (around 8 billion USD) excluding the automobile and bike segments.[5] Our conservative estimates imply that, through transactions in this particular retail chain only, about 20 million INR ($\approx$ 0.29 million USD) of demonetized notes retained their value without making their way into the taxable economy, while benefiting the retailer as well. If we scale up the estimates based on the ratio of the chain's yearly sales to the total retail market size, the estimated total impact of strategic transactions is at least 100 billion INR ($\approx$ 1.5 billion USD). This conservative estimate is still economically significant, as big as 21% of the annual state budget of Delhi in 2016. Bounded flexibility in supply-side strategic responses in our empirical context (compared to individual-owned businesses) suggests that the policy goal would have been even more affected if the stores could also be fully strategic and encourage more such transactions from households, which makes the estimated impact to be close to the lower bound.

We find heterogeneity in the size of strategic practices across stores to be correlated with the

[5] "The story of India's Rs 60,000 cr second-hand market, minus cars and bikes," The Economic Times, October 31, 2011.

size of local demonetization impact. This further reinforces our argument that these practices were explicit efforts by consumers to deal with the policy-induced shocks. The analysis also suggests that strategic transactions were not mainly driven by heterogeneous supply-side responses, which supports our identification strategy.

The paper offers implications to policy makers in three ways. First, we highlight the importance of understanding potentially wide spillover effects of government interventions that take place beyond the target group. Our paper empirically documents the presence of strategic consumers utilizing retailers in response to policy, and shows their significant impact on both retail profits and government policy outcomes. The incentive alignment between strategic consumers and retail stores, combined with its substantial impact on the intended aim of the policy, calls for careful policy design that incorporates the incentives of all relevant agents who are seemingly outside the core target of the policy. Although our empirical context features a large-scale demonetization policy whose frequency of occurrence is likely low, the lesson of how wide the scope of policy assessment should be can be extended to other policies like interest rates or privacy regulations, as media reports already suggest such spillovers.[6] As the marketing discipline has moved increasingly towards understanding policy outcomes (see Chandy et al. (2021) and Davis et al. (2021) for special issues on public policy and marketing), studying the unintended consequences of policies will become more important for a complete understanding of the policy initiative. Second, our results lay out new insights for policy makers aiming for economic transparency. Fighting against illicit financial flows and transitioning to a cashless society are major interests of many developing economies (OECD (2014), World Bank Group (2016)), and government-led policies, such as currency reforms, serve as tools that have been widely used to achieve such goals (Staehr (2015)). Therefore, our findings on unintended consequences have direct implications for policy makers and retailers whose

[6] "GDPR has been a boon for Google and Facebook," Wall Street Journal, June 17, 2019.

local economy is subject to the initiatives to raise economic transparency. Finally, we provide a new angle of assessing the impact of this particular demonetization policy. There have been many papers that evaluate the policy at the macro-level (Chodorow-Reich et al. (2019), A. Lahiri (2020)), but there has been little empirical research that looks at its consequences, intended or otherwise, with micro-level data. The paper adds value to this policy evaluation literature by delineating consequences of the policy in retail settings with a novel set of data.

We also document a new role for retailers in responding to and even absorbing some macro-level shocks. We observe that consumers' strategic transactions assign retailers the role of financial institutions by making them accept banned bills before the effective date and making them distribute legal notes to cash-strapped consumers. Although stores earn incremental revenues from strategic purchase expansion, they also pay the price by facing higher costs associated with more returns as well as with cash management. Market-level policies like interest rates would generate similar patterns in which retailers bear unintended policy-induced costs. The existing literature in economics and finance studies how monetary shocks gets transmitted to different agents, but its primary focus has been on the allocation between the financial sector and households/firms or its heterogeneous impact within the financial sector (Drechsler et al. (2017), Hoffmann et al. (2018)). Further research can explore how a macroeconomic shock is redistributed between retailers and consumers in various contexts, as well as the resulting equilibrium after strategic reactions by both sides.

Finally, the paper provides implications to retailers by shedding light on the scope of strategic consumer behavior. Extant literature has studied a variety of types of strategic consumer behavior, including waiting for lower prices (Song & Chintagunta (2003), Hartmann (2006), Nair (2007), Cachon & Swinney (2009), Soysal & Krishnamurthi (2012), Mantin & Rubin (2016), Aviv et al. (2019); See Aviv & Vulcano (2012) for review on dynamic list pricing) or for more information on product quality(Yu et al. (2016)). Building on this rich literature, our findings introduce a new form of strategic consumer behavior (strategic purchases and returns), thus broadening the scope of its potential impact on retailers. In particular, this is the first empirical paper that quantifies the impact of consumers utilizing retail policies to maximize their benefits. Many industries are suffering from increasing consumer abuses ranging from abuses of returns to dishonest charge disputes. Such actions are estimated to cost the U.S retail industries $15 billion a year (Robertson et al. (2020)). However, studying their consequences in academic research is particularly challenging as it is hard to find an exogenous shift that identifies strategic consumer practices separately from non-strategic ones. Most existing models in returns also do not separately model strategic returns from naive ones despite their different incentives and impacts on retail profit (E. T. Anderson et al. (2009), Petersen & Kumar (2015)). By providing empirical evidence of a large-scale effect of strategic consumer behavior on retailer performance, our analysis underscores that both retailers and researchers should be aware of potential moves by consumers when designing store policies, especially in the presence of macro-level shocks.

The rest of the paper proceeds as follows. Section 2 introduces the empirical context of the paper. Section 3 discusses model-free evidence of strategic purchases and returns. Section 4 and 5 sketch insights from a model of strategic consumer behaviors in response to the demonetization policy and discuss why different types of strategic behaviors lead to differential impacts on retail profit and policy outcomes. Section 6 explains our empirical strategy to separately identify such behaviors. Section 7 reports the estimation results and explores the source of store-level heterogeneity. Section 8 discusses the net impact of strategic consumer behaviors on retail profits and intended policy outcomes. Section 9 concludes.

# 2 Empirical context - Demonetization in India

## 2.1 Overview

On November 8, 2016, at 8:15 PM, the Government of India announced demonetization of all 500 and 1,000 INR banknotes and issuance of new 500 and 2,000 INR banknotes, effective as of the next day. The announcement was intended to be abrupt to block channels for money laundering in response to the policy. Only minimal information leak about the reform existed prior to the announcement.[7]

The demonetized banknotes could either be deposited to bank accounts over 50 days or be exchanged to new notes over the counter at all banks over 16 days. The latter option of exchanging at the counter had a strict limit of 2,000 to 4,000 INR per person per day (about 30 to 60 USD). Cash withdrawals from bank accounts were also restricted, and the withdrawal limit was not fully lifted until March 13, 2017.

## 2.2 Intended consequences and reported outcomes

The major goal of the policy was to fight corruption and clear black money in India by invalidating an unaccounted stock of money and bringing more money into the formal tax network.[8] The policy also intended to shift the economy towards a cashless society to further enhance economic transparency.[9]

Despite the intended benefits, a sudden withdrawal of high denomination notes levied a huge financial cost on the economy and created incentives for individuals to avoid such costs. Due to the short supply of the new notes, people could not easily exchange their banknotes through an official channel even after waiting for hours at the banks, which caused a critical impact in day-

[7] "Journalist broke story about currency demonetisation a fortnight back". Hindustan Times. 11 November 11, 2016.

[8] "Why Were the Notes Scrapped? RBI Chief, Economic Affairs Secy Explain". News18, November 8, 2016.

[9] "Goal Of Demonetisation: Modi's Promise Vs Jaitley's Defence". Bloomberg Quint, August 31, 2017.

to-day activities and in household finance.[10] The imminent shock, combined with the economy's heavy reliance on cash, heightened different incentives for people to exchange or utilize the old notes outside the official routes. One incentive was to avoid the physical cost of depositing or exchanging the old notes, as it was common for households to wait for hours in a lengthy queue at the banks and still fail to complete the task. The other incentive was to avoid depositing their cash for tax-related reasons, to either lower the amount of tax or reduce the penalty related to their previous tax evasion. Consistent with these underlying incentives, news articles reported that people indeed came up with numerous strategic ways to exchange or spend the demonetized notes via unofficial routes. One common strategy was to carry suitcases of demonetized bills to buy high-priced items.[11]

Statistics announced by the Reserve Bank of India (RBI) indicates that it is ambiguous whether the policy fully achieved its main objectives, which further calls for understanding the source of such ambiguity. According to the RBI data, 98.8 percent of the old currency notes were returned into the Indian banking system in about 6 months after the announcement of demonetization, although there was no significant increase in tax revenues due to the policy over the same time period (A. Lahiri (2020)). These numbers raise the question of whether the policy has effectively cleared black money or brought it to the taxable economy in the short run.[12] Abundant reports on strategic consumers suggest that consumers' deliberate transactions in demonetized cash at local retailers could be one of the forces that weakened the policy outcome.

In summary, individuals had an incentive to strategically exchange or utilize their old notes outside the official banking system - at retail stores in particular - in response to the demonetization policy. News articles imply that those strategic transactions could have had a major impact in

[10] "Crowds Line Up at India's Banks to Exchange Banned Rupee Notes". New York Times, November 10, 2016.

[11] "Indians Rush Frantically to Launder Their 'Black Money'", The New York Times, November 20, 2016.

[12] "Has Demonetization Achieved its Stated Objectives?" Madhyam, September 13, 2017.
"Demonetisation achieved objectives quite substantially: Govt." The Times of India, August 29, 2018.

diluting the intended policy outcome.

## 2.3 Data: Store-level transaction data before and after the demonetization policy

Using a retailer's store-level daily transaction data, we study whether people avoid the consequences of policy-induced shocks via strategic transactions. The data set contains over 7 million transactions from a large Indian retail chain dealing in with ticket items from 9/1/2015 to 12/31/2017.[13] The data period covers 14 months prior to demonetization and 13 months after demonetization. For each transaction-level observation, we observe the recorded date of invoice, price paid, payment method, the number of items, store ID, and whether or not the transaction is a return or a purchase. We also have addresses of all stores, which helps us collect demographic data around store locations. We do not have access to other item-specific or customer-specific information; the data set does not contain customer ID.

Among many payment methods available in the stores, card and cash are the two major modes of payment in the data, via which about 75% of daily sales are transacted. Other methods include checks, cash hires, commercial papers, credit notes, coupons, mobile wallet, and gift vouchers, and National Electronic Funds Transfer (NEFT) collection. For analysis, we group payment methods into three categories: Cash, Card, and Others.

Table 1 and 2 summarize the data. Median ticket price is around USD 61 and median quantity purchased is 1 (Table 1(a)).[14] There is a large variance across stores in the size of daily transactions as well as in the shares of different payment methods. Stores in the data set are located in 17 different cities (27 different districts), covering a wide range of demographics according to the

[13] We do not reveal the product category following the agreement with the data provider. Here, big ticket items refer to non-perishable products with high average ticket prices like jewelry, consumer electronics, large appliances, or high end saris and apparel.

[14] 1 USD = 67.92 INR on the day of policy announcement.

average rental prices of the store neighborhoods (Table 2).

**Table 1:** Summary statistics

(a) Transaction level

| | Min. | 1Q | Median | Mean | 3Q | Max. |
|---|---|---|---|---|---|---|
| Price paid (in USD) | 0.00 | 14.79 | 61.28 | 200.53 | 262.78 | 35672.33 |
| Quantity | 1.00 | 1.00 | 1.00 | 1.90 | 2.00 | 50001.00 |

(b) Store-level

| | Min. | 1Q | Median | Mean | 3Q | Max. |
|---|---|---|---|---|---|---|
| Av. daily sales (in USD) | 0.00 | 7630.14 | 12807.78 | 16621.71 | 20946.68 | 253620.07 |
| Av. daily sales (in quantity) | 0 | 96 | 144 | 174 | 215 | 50072 |
| Av. daily returns (in USD) | 0.00 | 376.10 | 1210.61 | 2140.56 | 2687.85 | 107624.56 |
| Av. daily returns (in quantity) | 0 | 4 | 9 | 13 | 16 | 2007 |
| Average % payment methods in daily purchases | | | | | | |
| Cash | 0.11 | 0.19 | 0.23 | 0.24 | 0.28 | 0.45 |
| Card | 0.29 | 0.46 | 0.54 | 0.52 | 0.57 | 0.73 |
| Other | 0.02 | 0.23 | 0.25 | 0.25 | 0.28 | 0.40 |
| Average % payment methods in daily returns | | | | | | |
| Cash | 0.14 | 0.23 | 0.27 | 0.29 | 0.34 | 0.56 |
| Card | 0.24 | 0.43 | 0.51 | 0.49 | 0.55 | 0.69 |
| Other | 0.01 | 0.20 | 0.23 | 0.23 | 0.26 | 0.36 |
| Average % (daily returns/daily purchases), by payment method | | | | | | |
| Cash | 0.01 | 0.09 | 0.12 | 0.12 | 0.15 | 0.27 |
| Card | 0.02 | 0.08 | 0.10 | 0.10 | 0.11 | 0.17 |
| Other | 0.01 | 0.08 | 0.10 | 0.11 | 0.13 | 0.19 |

**Table 2:** Store demographics

| | Min | 1Q | Median | Mean | 3Q | Max |
|---|---|---|---|---|---|---|
| Av. Rent (in USD) | 40.73 | 84.54 | 119.89 | 182.52 | 225.82 | 1009.22 |

| Location type | Number of stores |
|---|---|
| High Street | 55 |
| Mall | 33 |
| Others | 4 |

In the next section, we provide model-free evidence that suggests the existence of strategic returns and purchases.

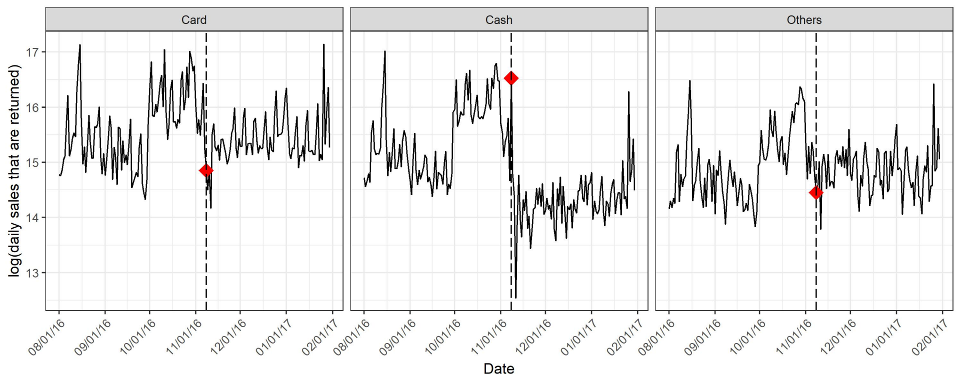
# 3 Model-free evidence of strategic consumer behavior

## 3.1 Strategic returns

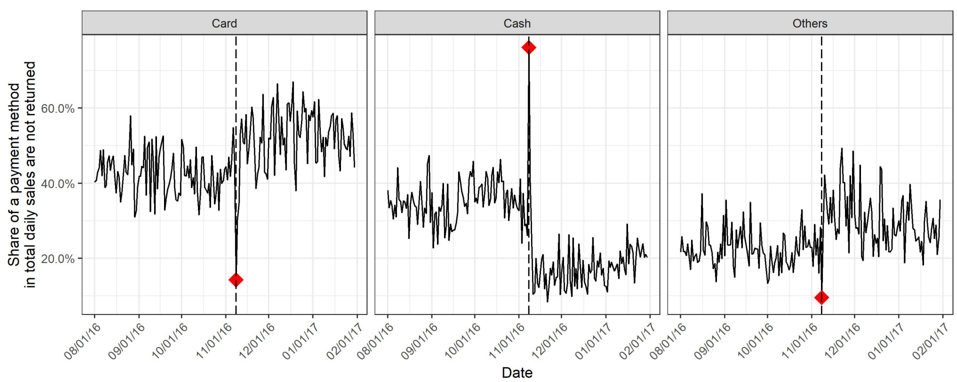
Figure 1 shows daily sales that are later returned and the shares of payment modes among those returned sales across all stores. Both are plotted based on the date of *original purchase* invoices, not based on the date of return invoices. On the day of policy announcement, there is a discrete jump in cash sales that are later returned (red dot in the middle panel). We observe the same pattern in the shares of payment methods (Figure 1(b)); among purchases that are made on the day of announcement and later returned, almost 80% are transacted with cash. An asymmetric increase in returns only among cash transactions is consistent with consumers' motivation to utilize banned notes and receive legal notes from the retailers, as only cash sales can be refunded in cash according to the chain's refund policy. These strategic returns not only hurt the policy aim by allowing households to switch the demonetized notes to new notes without depositing them into the bank accounts, but also impose additional burdens to the retail stores by increasing the costs associated with returns.

Figure 2 suggests that the policy announcement affects consumer decisions on whether to return rather than when to return. Although there is a noticeable surge of returned sales in cash if we plot them based on the original purchase dates (Figure 2, solid line), there is no bunching in returns based on the actual returned date (Figure 2, dashed line). Unlike in the case of purchase acceleration in which the timing of purchases is manipulated, the data show no evidence of shifts in the timing of returns due to the policy announcement. Instead, it indicates that the policy announcement changes consumers' willingness to return any purchased items.

The increase in returns of cash sales is more prominent among larger invoices, which further supports consumer incentives to receive legal notes from the retailer. Figure 3 shows the shares




**(a)** Daily sales that are later returned, by payment method




**(b)** Share of payment methods in daily sales that are later returned

**Figure 1:** Aggregate daily returns and return rates by payment method (using the date of original purchase invoices)

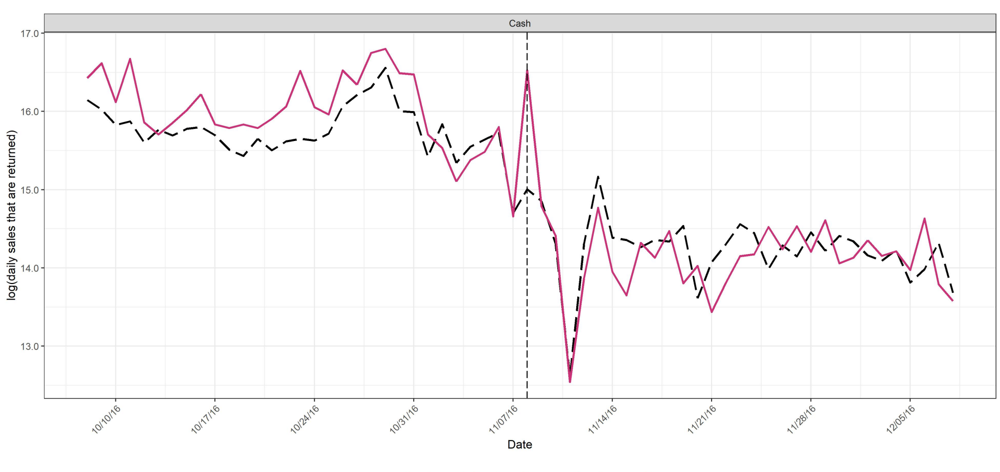



**Figure 2:** Aggregate daily cash sales that are later returned, by original purchase dates and by return dates

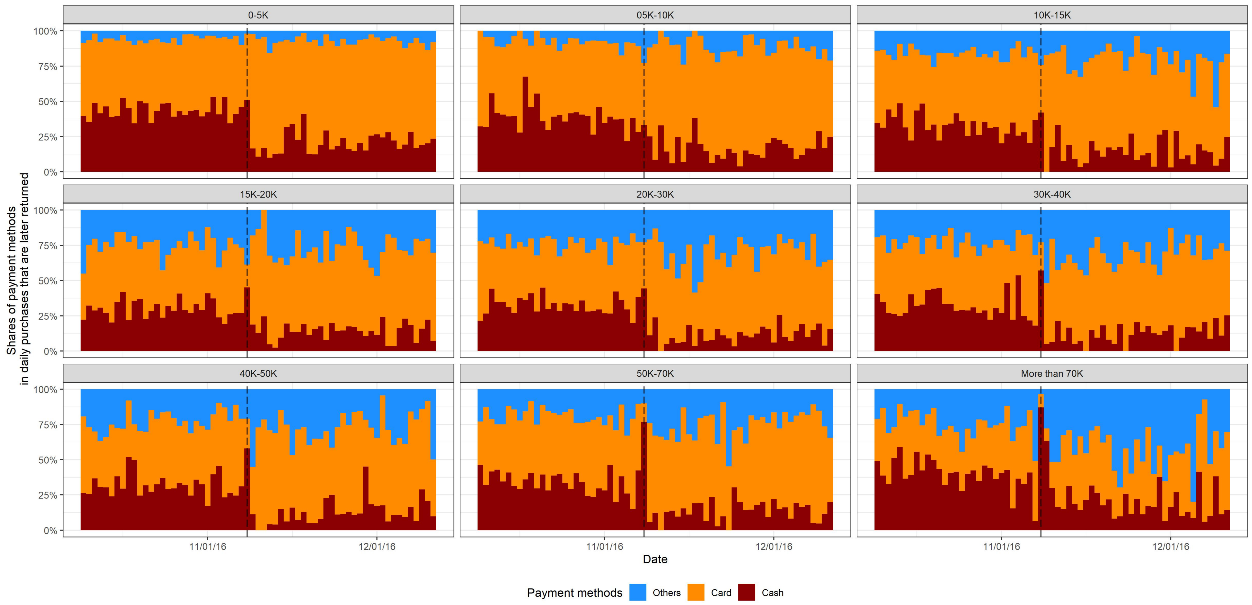



**Figure 3:** Share of payment methods in returned sales, by invoice size (from 10/10/2016 to 12/11/2016)

of payment methods in daily sales that are later returned, grouped by invoice sizes. We group individual transactions into 9 categories based on the net price paid per transaction (in INR): 0-5K, 5-10K, 10-15K, 15-20K, 20-30K, 30-40K, 40K-50K, 50K-70K, and more than 70K. Among sales that are made on the day of policy announcement and are later returned, the share of cash transactions goes up drastically only for larger-size invoices (the top left cell vs. the bottom right cell of Figure 3). This offers suggestive evidence that consumers strategically return high-price items that are bought with cash prior to demonetization to receive the new notes from the retailers.

Figure 4 illustrates large store-level heterogeneity in the size of strategic returns. Four sample stores show different sizes of the net increase in returns of purchases made in cash on the day of announcement, suggesting that certain stores experience more strategic returns than others.

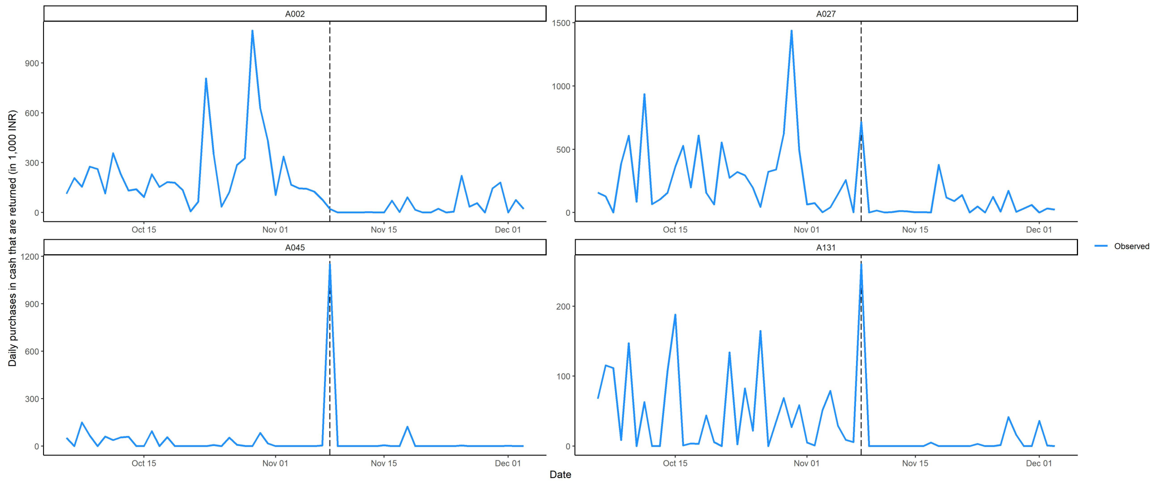


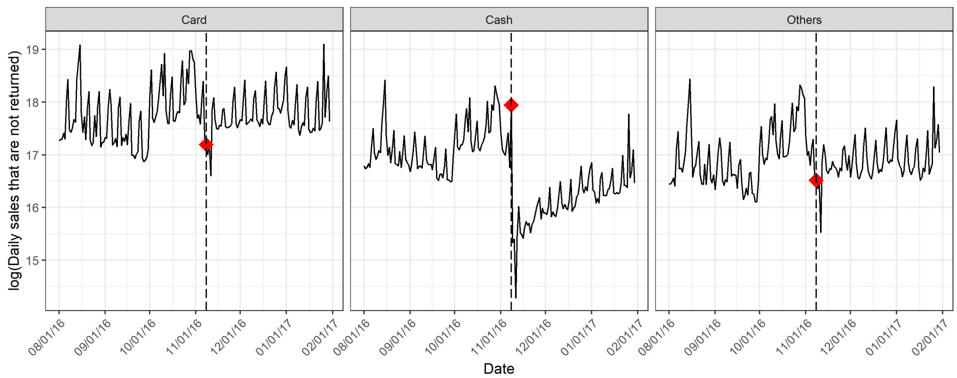

**Figure 4:** Daily sales in cash that are later returned, by store

## 3.2 Strategic purchases

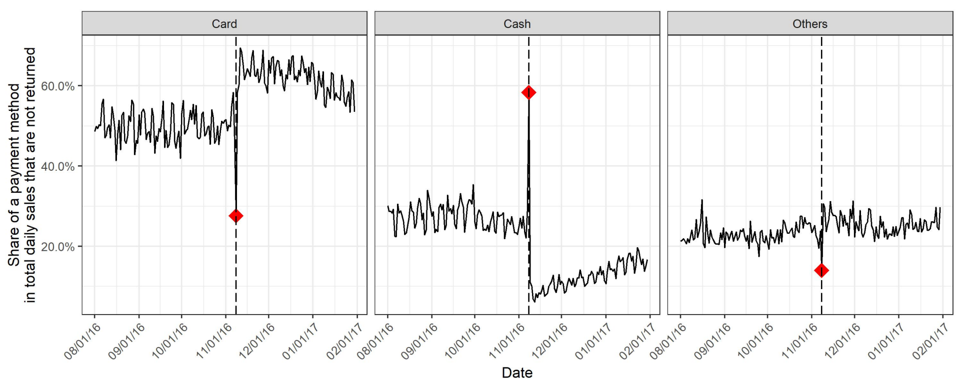
Figure 5 presents daily final purchases and the shares of payment modes across all stores before and after the policy. Recall that final purchases refer to purchases that are not later returned. Red dots denote the observations on the day of policy announcement. The plot shows a discrete jump in final purchases made with cash on the day of policy announcement (Figure 5(a)).[15] Strategic choices of cash as a payment method are even more prominent when we look at the shares of payment methods on the day of announcement (Figure 5(b)). The immediate surge of cash purchases matches the predicted pattern when households buy more products to spend demonetized bills.

As we discuss in Section 2.2, the increase in unreturned cash sales on the day of announcement can arise from different incentives for households to save several types of policy-induced costs. First, purchase acceleration to use up demonetized bills can cause the net sales increase on the day of announcement as households are willing to avoid waiting for hours at banks to exchange or deposit the notes. Second, purchase expansion can result in the net increase in sales because households try to avoid depositing their holdings of cash to their bank accounts for tax-related

[15] Overall increase in sales in October 2016 is due to seasonality (Diwali and Dussehra).




**(a)** Aggregate daily final purchases, by payment method




**(b)** Shares of payment methods in aggregate daily final purchases

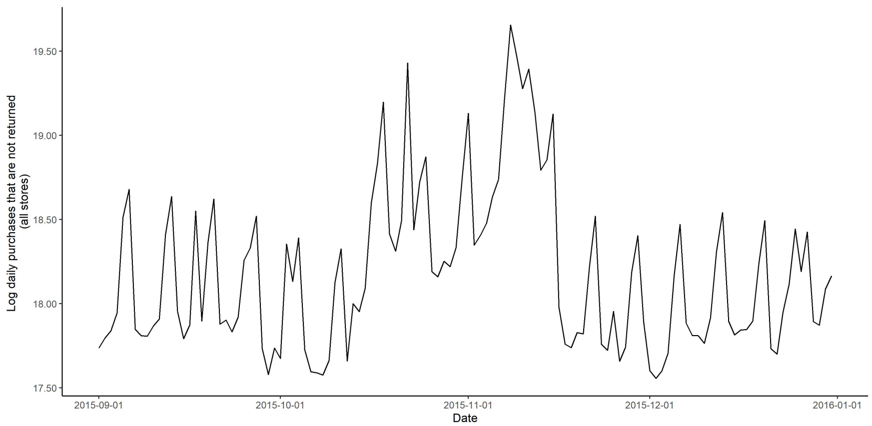
**Figure 5:** Aggregate daily final purchases and the shares of payment methods in daily final purchases

reasons. Both profit and policy implications differ across the two incentives. Purchase acceleration neither increases long-term profit of the retail chain nor affect the policy goal, as those purchases are merely expedited and not additionally created due to the policy. However, purchase expansion benefits the retail chain with higher revenues, while canceling out the policy maker's intended consequence of increasing cash deposits. The two different incentives predict different empirical patterns of net sales after demonetization; while purchase acceleration forecasts a dip in sales that follows the discrete jump, purchase expansion does not expect any (Hendel & Nevo (2003)).

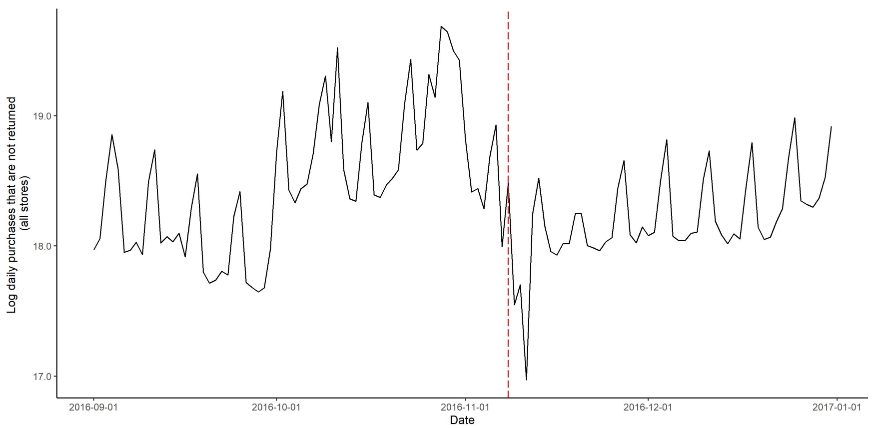
To further decompose the surge of net sales in cash into accelerated and incremental purchases, we check whether there is any short-term dip in total final sales after the day of announcement (Figure 6). Total final sales sharply decrease right after the day of announcement, which is consistent with the predicted pattern under purchase acceleration. The dip is salient when we compare the sales trends around the same time across different years.[16] However, the level of daily net purchases seems to fully recover in few weeks after the announcement, indicating that the degree of purchase acceleration does not exceed a month at the chain level if any.

As in the case of returns, final purchases in cash on the day of announcement soar among high-ticket items, which aligns with households' strategic incentives to utilize the old notes. Figure 7 reports the shares of payment methods in daily purchases grouped by invoice sizes. The graph shows that, among the unreturned purchases whose ticket sizes are greater than 70K INR, the share of cash transactions reaches almost 80% on the day of announcement (the bottom right cell of Figure 7). In contrast, there is no significant increase in cash final purchases among small ticket items (the top left cell of Figure 7). This suggests that the large increase in final cash purchases on the day of announcement results from the strategic incentives to spend the old notes before they get demonetized.

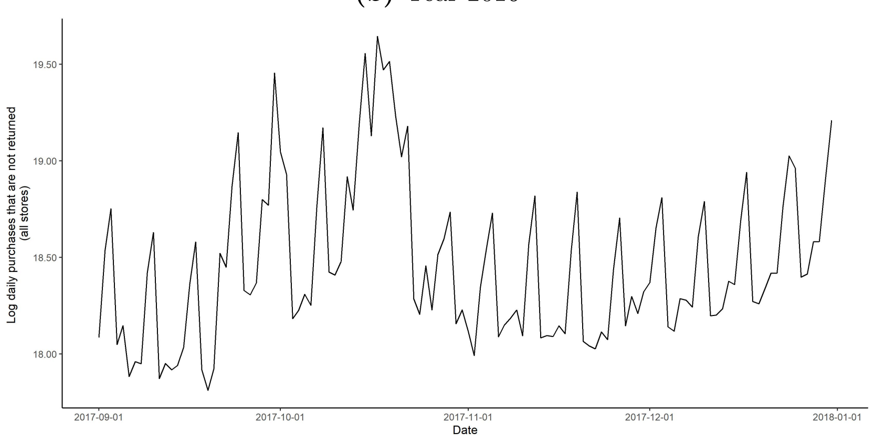
[16]There is a shift in time periods with an increase in sales over years because Diwali and Dussehra, two major




**(a)** Year 2015




**(b)** Year 2016




**(c)** Year 2017

**Figure 6:** Daily total final sales across all stores. Dashed line marks the day of policy announcement.

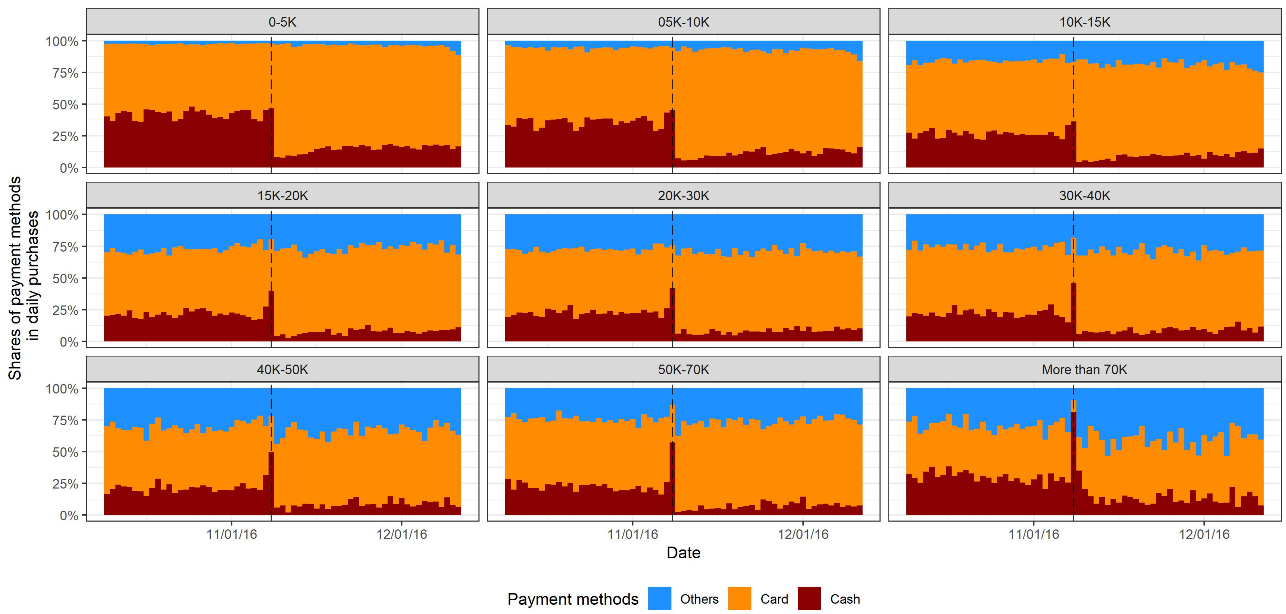



**Figure 7:** Shares of payment methods in daily purchases, by invoice size (from 10/10/2016 to 12/11/2016)

The size of strategic purchases seems to vary significantly across the stores (Figure 8). While one store reports no prominent increase in cash purchases on the day of policy announcement, other three stores display visible peaks on the same day. Furthermore, even those three stores with peaks in cash sales show difference in the heights of the peaks relative to the variance of daily sales. Along with Figure 4, the plot underlines the importance of analyzing the effect of strategic behavior to be store-specific.

# 4 Consumer incentives for strategic purchases and returns

With model-free evidence in hand, we introduce a simplified model in the Appendix (Section A.1) to explore how households' different incentives to minimize the shock from demonetization generate such observed increases in returns and purchases. We do not sketch any strategic responses of retailers in this model as the abruptness of the policy enactment allows us to assume that there is no

holidays in India, vary in their calendar dates across years.

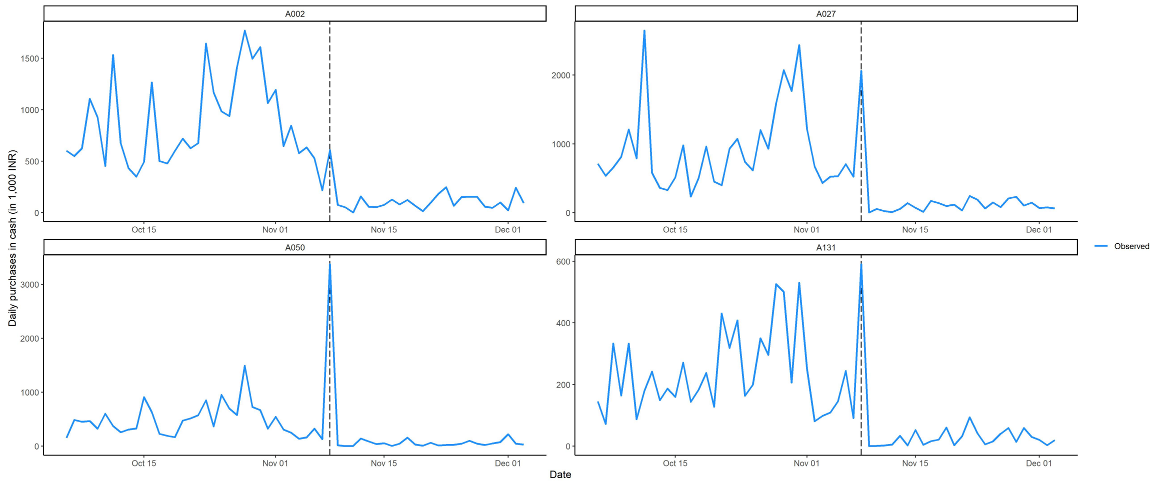



**Figure 8:** Daily final purchases in cash, by store

overnight response by the retail chain, which we also confirm reviewing news articles. Future work may extend the framework and incorporate the supply side decisions to understand an equilibrium outcome when both households and firms are expected to react simultaneously.

The model explains consumer incentives for four different types of strategic transactions: strategic returns, incremental final purchases, accelerated purchases, and switching to cash. Here, we outline the main intuitions from the model in words.

**1) Strategic returns** Households can save on tax penalty by making purchases with soon-to-be demonetized cash notes and returning the items to receive legal notes from the retailer. For some households whose demonetized cash holding is not large, such strategic returns can even save the cost of visiting banks by converting all cash in hand to legal notes at the retailer. The model shows that $R_i$, the amount of money that is converted to legal notes via strategic returns, does not have to be deposited to bank accounts and thus can stay outside the formal tax network. As illustrated in Equation (A.0.6), this saves household income in three different ways: 1) by reducing the amount of tax to be paid, 2) by reducing the penalty attached to former tax evasion, and 3) by removing the depositing cost (e.g., the cost of waiting at the banks) if all demonetized cash can be converted to legal notes at the retailer via strategic returns. Here, we do not assume any frictions or cost associated with the return activity itself, including the cost of multiple store visits.

Although strategic returns would give the highest utility to households given the policy, a strict return policy does not always guarantee that such returns can take place. Although any purchased items can be returned in 7 days if there are any issues with the products according to the store managers we contacted, anecdotal evidence suggests that the refund option for simple change of mind is rarely available. Also, even the most generous refund policy in the market still requires certain conditions to be met like intact packaging. This implies that, among people who made purchases on the day of announcement before the policy information became public, only those who did not open the package could attempt to return the purchased items which was not always successful. Even those people who made purchases after the policy announcement before the effective date purely for strategic purposes had to go through the stringent return process that not everyone could complete.

**2) Incremental final purchases** For households who have evaded a large amount of tax before the policy, it can still be beneficial to convert soon-to-be demonetized notes to physical products even if the option of return is not available, since such purchases lower post-policy tax and tax penalty. The model (Equation A.0.7, A.0.8) implies that it is beneficial for households to even "discard" demonetized cash via incremental purchases as long as the discarded cash value is less than the resulting savings they get from a lower tax penalty and zero depositing cost. This is consistent with households' physical abandonment of demonetized cash without depositing it, which is documented in press reports:

> "Some have thrown in the towel, rather than risking an investigation into their taxes, filling pillowcases and paper bags with the old currency and dumping them in the trash.

> Notes of 1,000 rupees, the equivalent of about \$15, have been spotted floating down the Ganges River."
>
> "Indians Rush Frantically to Launder Their 'Black Money,'" The New York Times, Nov. 20, 2016.

The model also shows that incremental purchases in response to the policy can be larger when reselling purchased items is allowed (Equation A.0.8). Given that most transactions in the second-hand market are not recorded in any taxable accounts, reselling incrementally purchased items in the second-hand market not only encourages further incremental purchases but also increases the amount of cash off the official tax radar.

**3) Accelerated final purchases** Households without any tax evasion still have incentives to make intertemporal substitution and save on the costs of visiting banks to deposit cash. The model shows that households are willing to accelerate their purchases in cash as long as the cost of intertemporal substitution is smaller than the savings from the depositing cost. For the condition to be met, households should be able to use up the entire cash holdings via accelerated purchases, as the depositing cost becomes zero only when there is no cash holdings left to be deposited. Also, the discount factor should be small enough to be outweighed by the benefit from not depositing the banned bills, which limits the degree of purchase acceleration.

**4) Strategic choices of payment method (switching to cash)** Finally, households originally planning to make purchases on the day of announcement can switch to cash from other payment methods to use the cash notes that are about to be demonetized. Here, there is no intertemporal substitution as the purchase is originally planned to take place on the day of announcement.

Section A.1 also discusses how these strategic actions are incorporated in the retailer's profit function (Equation ()), whose implications are elaborated more in detail in the following section.

# 5 Differential effects of strategic transactions on retail profit and policy outcomes

Each action differs not only in its incentive but also in its impact on retail profits and policy outcomes. Table 3 summarizes the direction of impact in each case.

**Table 3:** Impact of strategic consumer behavior

| | Retail profit | Policy outcome |
|---|---|---|
| Strategic returns | Negative | Positive/Negative |
| Incremental final purchases | Positive | Negative |
| Accelerated final purchases | No effect | No effect |
| Switching to cash | No effect | No effect |

Strategic returns have a negative impact on retail profit because a hike in product returns burdens retailers with higher costs associated with it (Robertson et al. (2020)). As illustrated in Equation (A.0.6), returns allow households to shade their income by securing legal notes that do not have to be deposited or exchanged, which is directly against the policy objective. However, these returns also support the demonetization policy in a way by making retailers distribute legal notes and thus absorb market shocks triggered by the imminent cash shortage.

Both accelerated final purchases and switching to cash do not have any significant impact on retail profit and policy outcome, as those purchases would have been made regardless of the policy enactment by definition. Incremental final purchases, while increasing retail profit, result in a negative impact on the policy outcome by providing a route to reduce post-policy tax and tax penalties (Equation (A.0.7) and (A.0.8)). Moreover, such transactions also leave cash in the informal economy, as households can receive legal notes by reselling the items in the second-hand market which is not integrated into the formal economy.

Because of the differential impacts, it is critical for researchers to separately identify the four actions to analyze their net impact. In the next section, we discuss how we identify such behaviors from the observed transaction data.

# 6 Identification and empirical methodology

## 6.1 Identification of strategic consumer behaviors

Table 4 maps different types of strategic behaviors into the observed data counterparts.

**Table 4:** Identification of different strategic behaviors

| | Strategic behavior | Identification from the data (store-level daily transactions) |
|---|---|---|
| Returns | Incremental returns | A spike in returns of items that are purchased with cash on the day of announcement |
| Final purchases | Substitution to cash | Change in non-cash purchases on the day of announcement |
| | Accelerated purchases | A dip in total sales after the policy enactment |
| | Incremental purchases | A spike in cash purchases net of substitution to cash and accelerated purchases |

**Identification of strategic returns.** Strategic returns are identified as an increase in returns of products that are purchased with cash on the day of announcement. If the policy announcement raises the incentives to return, we expect to see more returns among the items that are purchased with cash on the day of announcement. As the policy affects households' decisions on whether to return instead of when to return (Figure 2), we analyze the return data based on the original purchase dates. Figure 9 visualizes the identification strategy. A solid line represents hypothetical returns of cash purchases based on the original purchase dates. Strategic returns, marked as $R$, is identified as the gap between the counterfactual returns (horizontal dashed line) and the observed returns on the day of announcement (red dot).

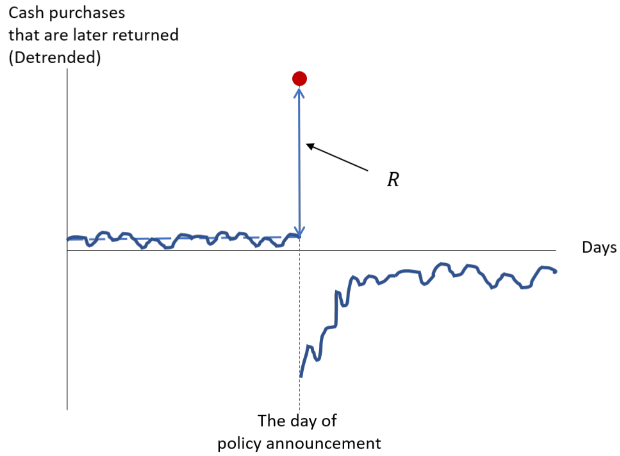
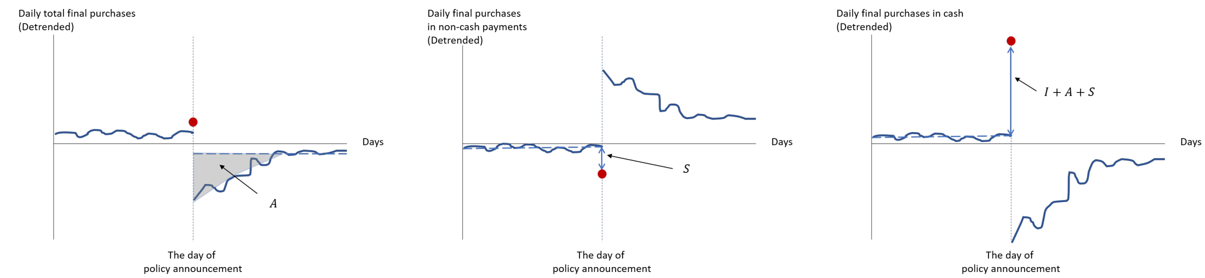



**Figure 9:** Identification of strategic returns from observed daily returns of cash purchases

**Identification of strategic final purchases.** To measure the size of accelerated purchases, we use the prediction of household inventory models: if there is purchase acceleration, it should be followed by a drop in aggregate sales whose size matches the amount of accelerated purchases (See Hendel & Nevo (2003) for review). Relying on this key assumption, we first recover accelerated purchases ($A$) by estimating the size of the dip in total final sales after the policy announcement. Next, we identify substitution to cash from other non-cash payment methods ($S$) as a decrease in non-cash purchases on the day of policy announcement. The assumption here is that any negative deviation in non-cash final purchases is transferred to net sales in cash on the day of announcement. Finally, we quantify incremental final purchases ($I$) by subtracting accelerated purchases ($A$) and switching to cash ($S$) from the the deviation in cash final sales on the day of announcement. Figure 10 illustrates the process. Like in Figure 9, solid lines represent hypothetical data on daily total purchases, non-cash purchases, and cash purchases that are not returned respectively. Horizontal dashed lines represent counterfactual daily purchases without strategic transactions, and the red dots represent the observed outcomes on the day of policy announcement. Each type of strategic purchases is identified as a function of the gap between the observed and counterfactual daily purchases in different payment methods.




**(a)** Accelerated final purchases ($A$) identified from daily final purchases **(b)** Switching to cash ($S$) identified from daily final purchases in non-cash payments **(c)** Incremental final purchases ($I$) identified from daily final purchases in cash

**Figure 10:** Identification of strategic purchases from observed final purchases

## 6.2 Empirical methodology

Given the large variation across stores in their locations and demographics, we estimate the four types of strategic behaviors by store. We recover population distributions of strategic returns and purchases by analyzing each store's daily transaction data separately. In other words, for each strategic behavior, we obtain a set of 92 estimates from different stores.

Our estimation approach is similar to the bunching approach recently developed in economics, which studies behavioral responses of individuals triggered by discontinuities in the available choice sets (See Kleven (2016) for review). The traditional bunching approach is used when individuals' incentives are expected to generate bunching at a particular threshold which is joined by the missing mass following the spike. It first obtains a counterfactual distribution of individuals' choices by fitting flexible polynomials to the data that exclude the observations affected by such behavioral responses. The size of bunching is then estimated as the difference between the counterfactual fitted values and the observed data over the range of interest, which is similar to what we illustrate in Figure 9 and Figure 10.

Our approach is different from the bunching approach in two ways. First, unlike in most empirical studies that apply the bunching approach to cross-sectional data, we use time-series data. This implies that construction of counterfactual values should explicitly incorporate the time-series nature. To do so, in addition to flexible polynomials that capture time trends and seasonal effects, we include lagged outcome variables and forecast error terms to fit an ARIMA model when computing counterfactual values. Second, we separately identify the size of bunching that comes from the missing mass (accelerated final purchases) and the size of bunching that is generated in addition to the missing mass (incremental final purchases). The traditional bunching approach matches the size of the observed bunching to the size of the following missing mass to identify the region affected by behavioral responses. As one of our estimation goals is to disentangle incremental final purchases from accelerated final purchases that are reflected in the subsequent sales dip, we allow the size of the observed bunching in cash purchases to be larger than the missing mass in sales after demonetization. Specifically, we identify accelerated purchases as the size of the missing mass (sales dip) and estimate incremental purchases by subtracting the estimated accelerated purchases from the observed bunching in cash purchases on the day of announcement. To recover in which period the sales dip ends, instead of finding where the size of missing mass matches the observed bunching, we find a point where numerical derivative of the de-trended sales data gets close to zero after the sales dip.

Following the bunching literature, we calculate standard errors for the estimated strategic behaviors using a parametric bootstrap procedure. Bootstrapping gives us store-specific standard errors for strategic returns and purchases, which is needed to test whether the estimated strategic transactions are statistically significant for each store given the wide heterogeneity across the stores (Figure 4 and 8). Bootstrapped standard errors tell us whether the estimates we obtain are within the range of residuals that are not explained by the model.

We fit a flexible time-series model to compute predicted values and add randomly resampled residuals to construct a large number of bootstrap samples. For this approximation to work, the residuals to be resampled must be i.i.d and should be re-centered to prevent a random bias that does not goes to zero in the limit (S. N. Lahiri (2003)). We test the i.i.d property of the residuals by checking the autocorrelation function.

**Estimation of strategic returns.** For each store, we take the following steps to estimate strategic returns.

1. **Compute counterfactual returns by fitting a time-series model with seasonal effects to the observed return data.** We run the following regression on returns of purchases with cash:

$$
\begin{aligned}
&\text{For } t \in \{t|1 \leq t \leq T \text{ and } t \neq t_0\},\\
&r_{sct} = \sum_{p=1}^{p_1} \Gamma_{sp}\text{Diwali}_t^p + \sum_{p=1}^{p_2} \Theta_{sp}\text{Dussehra}_t^p + \sum_{p=0}^{p_3} \Psi_{si} t^p + \sum_{p=1}^{p_4} B_{sp} r_{sc,t-p} + \sum_{p=1}^{p_5} \Phi_{sp}\epsilon_{sc,t-p}\\
&\qquad + \sum_m \mathbf{1}\{\text{Month} = m\} M_{sc} + \sum_w \mathbf{1}\{\text{Day of week} = w\} T_{sc} + \epsilon_{sct}\\
&\qquad = \widehat{f}(X_{st}, t) + \epsilon_{sct} \qquad (1)\\
&\widehat{r}_{sct_0} = \text{Counterfactual returns on the day of policy announcement with no strategic returns}\\
&\qquad = \widehat{f}(X_{st_0}, t_0). \qquad (2)
\end{aligned}
$$

$t_0$ denotes the day of policy announcement, and $r_{sct}$ denotes the returns whose original purchases are made with cash at store $s$ in day $t$. $t$ is the date of original purchases, not the date of actual returns. $\text{Diwali}_t$ and $\text{Dussehra}_t$ control for seasonality around two big holiday seasons in India. $\text{Diwali}_t$ ($\text{Dussehra}_t$) is 1 for $t$ that are 14 days prior to the day of Diwali (Dussehra), increases up to 20, and is set to be 0 outside this 20-day window. We set $p_1$ and $p_2$ to be 3 but try different orders of polynomials up to 5 for robustness check. The order of the polynomial to control for time trends ($p_3$) is chosen by the Bayesian Information Criterion

(BIC).[17] $\widehat{r}_{sct_0}$ is the predicted counterfactual returns on the day of announcement and is the fitted value of the model we estimate with the *data that excludes the day of announcement.*

We remove any potential autocorrelations by including lagged returns and lagged forecast errors whose order is chosen by BIC.[18] We check autocorrelation function plots of the resulting residuals $\epsilon_{sct}$ for each store to confirm that serial correlation is removed.

2. **Generate bootstrap samples of counterfactual returns.** We draw a random sample $\epsilon^b_{sc1}, \ldots, \epsilon^b_{scT}$ from the residuals $\{\epsilon_{sc1}, \ldots, \epsilon_{sct_0-1}, \epsilon_{sct_0+1}, \ldots \epsilon_{scT}\}$, re-center them on 0, and add them to $\widehat{r}_{sct}$ to construct counterfactual bootstrap samples. Each element of replicate sample $b \in [1, B]$ is constructed as

$$r^b_{sct} = \widehat{r}_{sct} + \nu^b_t \epsilon^b_{sct} \tag{3}$$

$$\text{where } \nu^b_t = \begin{cases} -1 & \text{with probability } \frac{1}{2} \\ 1 & \text{with probability } \frac{1}{2}. \end{cases}$$

3. **Obtain estimates of strategic returns as the difference between the observed and counterfactual residual returns.** We obtain the estimate of strategic returns ($R_s$) and its standard error by subtracting the counterfactual returns on the day of announcement ($r^b_{sct_0}$ in Step 2) from the actual observed returns ($r_{sct_0}$).

$$R_s = r_{sct_0} - \frac{1}{B}\sum_b r^b_{sct_0}. \tag{4}$$

[17]We choose the degree of polynomials that gives the highest BIC among $p_3 \in [1, \ldots, 9]$.

[18]We choose a pair of $p_4$ and $p_5$ in Equation 1 that gives the highest BIC among $(p_4, p_5) \in \{(1,1), \ldots, (1,5), (2,1), \ldots, (5,5)\}$.

**Estimation of strategic purchases.** We take the following steps to separately estimate three types of strategic final purchases: accelerated purchases, switching to cash, and incremental purchases.

1. **Compute counterfactual purchases by fitting a model with seasonal effects and autocorrelation to the observed final purchases data.** For total daily purchases, daily cash purchases, and daily non-cash purchases, we run the following regression separately :

$$
\begin{aligned}
&\text{For } t \in \{t | 1 \leq t \leq T \text{ and } t \neq t_0\} \text{ and } k \in \{\text{All, Cash, Card, Others}\},\\
&y_{skt} = \sum_{p=1}^{p_1} \gamma_{sp} \text{Diwali}_t^p + \sum_{p=1}^{p_2} \theta_{sp} \text{Dussehra}_t^p + \sum_{p=0}^{p_3} \psi_{sp} t^p + \sum_{p=1}^{p_4} \beta_{sp} y_{sk,t-p} + \sum_{p=1}^{p_5} \phi_{sp} \iota_{sk,t-p}\\
&\qquad + \sum_m \mathbf{1}\{\text{Month} = m\} \mu_{sk} + \sum_w \mathbf{1}\{\text{Day of week} = w\} \tau_{sk}\\
&\qquad + \sum_{p=1}^{p_6} \mathbb{1}\{t \in [t_0+1, t_0+60]\} \xi t^p + \iota_{skt}\\
&\quad = \widehat{g}(X_{st}, t) + \mathbb{1}\{t \in [t_0+1, t_0+60]\} P_{skt} + \iota_{skt} \qquad (5)\\
&\widehat{y}_{skt_0} = \text{Counterfactual purchases in payment method } k \text{ on the day of policy announcement}\\
&\qquad \text{with no strategic purchases}\\
&\quad = \widehat{g}(X_{st_0}, t_0) \qquad (6)
\end{aligned}
$$

$y_{skt}$ denotes final purchases made with payment method $k \in \{\text{All}, \text{Cash}, \text{Card}, \text{Others}\}$ at store $s$ on day $t$. $P_{st,All}$ captures the distortion in daily sales for 60 days after the policy announcement due to strategic purchase acceleration. It is modeled as the polynomials of $t$ over a 60-day window after $t_0$.[19] $\widehat{y}_{skt}$ is the predicted counterfactual purchases in payment method $k$ on the day of announcement; it is the *fitted value of the model we estimate with*

[19]The order $p_6$ is set to be 5. The results stay qualitatively the same when we try different orders of polynomials from 3 to 7.

*the data that excludes the day of announcement.* All the other right-hand side variables are defined as in Equation (1). We check autocorrelation function plots of the resulting residuals $\iota_{sct}$ for each store to confirm that serial correlation is removed.

2. **Find where the sales dip ends.** Using the estimated $P_{st,All}$ for $t \in [t_0 + 1, t_0 + 60]$, we identify the end of the sales dip as the time period in which numerical derivative of the fitted $P_{sk,All}$ becomes close to 0 for the first time after the day of announcement. Let $t'$ denote when the sales dip comes to an end.

3. **Generate bootstrap samples of counterfactual purchases.** For each $k \in$ {All, Cash, Card, Others}, we draw a random sample $\iota^b_{sk1}, \ldots, \iota^b_{skT}$ from the residuals $\{\iota_{sk1}, \ldots, \iota_{skt_0-1}, \iota_{skt_0+1}, \ldots, \iota_{skT}\}$, re-center them on 0, and add them to $\widehat{y}_{skt}$ to construct counterfactual bootstrap samples. Each element of bootstrap sample $b \in [1, B]$ is constructed as

$$y^b_{skt} = \widehat{y}_{skt} + \nu^b_t \iota^b_{skt} \tag{7}$$

$$\text{where } \nu^b_t = \begin{cases} -1 & \text{with probability } \frac{1}{2} \\ 1 & \text{with probability } \frac{1}{2}. \end{cases}$$

4. **Obtain estimates of strategic final purchases.** We estimate the three types of strategic

final purchases and their standard errors using the observed and counterfactual purchases:

$$A_s = \text{Accelerated purchases } = \sum_{t=t_0+1}^{t'} \left( \frac{1}{B} \sum_b \widehat{y}_{st,all}^{b} - y_{st,all} \right), \tag{8}$$

$$S_s = \text{Switching to cash } = \sum_{k \in \{\text{Card, Others}\}} \left( \frac{1}{B} \sum_b \widehat{y}_{skt_0}^{b} - y_{skt_0} \right), \tag{9}$$

$$I_s = \text{Incremental purchases } = y_{st_0,cash} - \frac{1}{B} \sum_b \widehat{y}_{st_0,cash}^{b} - \mathbb{1}\{A_s > 0\}A_s - \mathbb{1}\{S_s > 0\}S_s. \tag{10}$$

To prevent the overestimation of incremental final purchases, we subtract estimated accelerated purchases ($A_s$) and switching to cash ($S_s$) from the final cash purchases only when $A_s$ and $S_s$ are positive.

## 6.3 Discussion

Unobserved market practices and conditions may introduce measurement errors to our estimates. First, the demonetization shock led to short-term reduction in the entire consumption basket due to the turbulence and uncertainty in the market (Wadhwa (2019)), which we do not explicitly incorporate in our estimation. Second, backdating of invoices was reported to be prevalent shortly after the announcement as households carried bags of demonetized notes and asked stores to accept them. [20] Although we do not find reasons for these conditions and practices to affect our estimates of strategic returns, it is possible that our estimates of strategic purchases have biases because the estimation procedure does not separately identify those practices and economic downturn when decomposing different types of strategic purchases, namely purchase acceleration and incremental purchases. (Note that our estimates of payment switching do not get affected by potential biases due to backdating as it is identified as the decrease of *credit card purchases* on the day of announcement.)

[20] "Indians Rush Frantically to Launder Their 'Black Money,'" The New York Times, November 20, 2016.

Section A.2 in the Appendix discusses empirical evidence that suggests measurement errors from back-dated receipts would not affect our estimates significantly. First, we emphasize that the data provider is a large retail chain that does not allow store managers to access and manipulate invoice information. To give empirical evidence on this, we analyze the sequence of invoice numbers that were generated around the time of policy announcement. If a large amount of back-dated invoices were issued after the policy became effective, we should be able to see the order of system-generated invoice numbers being shuffled around the day of announcement, as in fact those back-dated invoices were generated later than the invoices that were truly issued on the day of announcement. Our data show that the receipt numbers are all aligning in an ascending order when we group them by invoice dates, rejecting this hypothesis. Second, we show similar patterns of strategic purchases in a different product category with hourly time stamps, which suggests that many households indeed rushed to nearby stores after the 8 PM announcement to use up their soon-to-be-demonetized cash before the policy became effective.

More importantly, these unobserved market factors and retailer practices turn our estimates of strategic incremental final purchases, which has the most direct negative effect on the intended policy outcome out of all strategic transactions, to be strictly conservative estimates. From a methodological point of view, as we attribute any short-term decline in sales entirely to purchase acceleration, our empirical strategy returns liberal estimates of accelerated purchases which in fact is a combination of accelerated purchases, overall decline in economic activities, and backdated invoices. This leads us to get conservative estimates of incremental purchases which we recover by subtracting accelerated purchases from the observed cash purchases on the day of announcement net of seasonality (Equation 10). If we obtain statistically and economically significant estimates even in this conservative approach, the results would further strengthen our finding that households' strategic shopping behavior had a significant impact on the policy goal. From a substantive point of

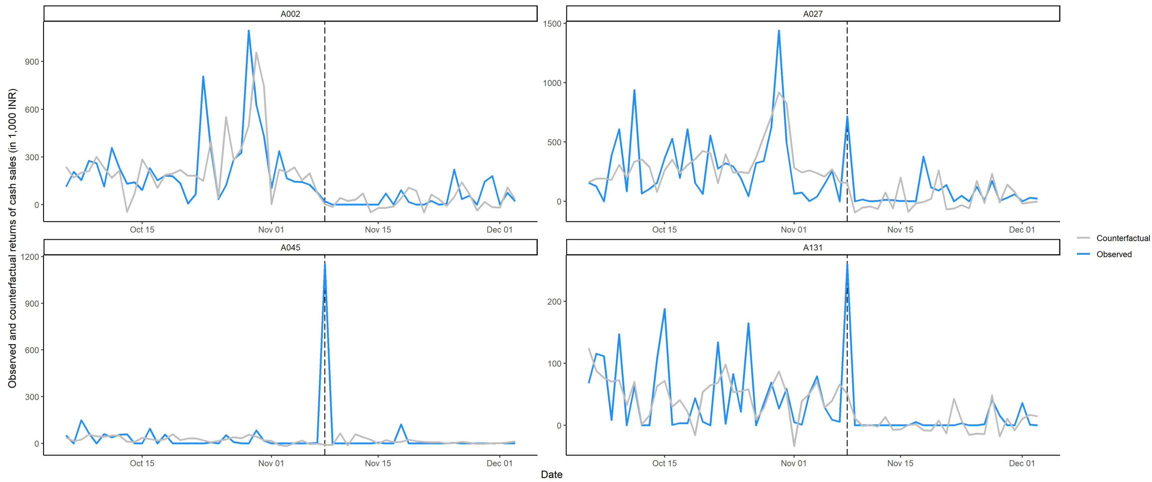



**Figure 11:** Observed and counterfactual returns in sample stores

view, if there was backdating of invoices, then it further strengthens our argument that households intentionally made such transactions with already demonetized notes, even illegally, to avoid tax and/or save the waiting cost at the banks.

To understand the possible range of true incremental cash purchases given our conservative estimation approach, we also report an upper bound of the incremental purchases, which is the estimated total increase in cash purchases on the day of policy announcement without further decomposition.

# 7 Estimation results

## 7.1 Strategic returns

Figure 11 compares the observed returns to the counterfactual returns under no strategic behavior for a sample of stores. The size of the gap between the counterfactual and the observed returns on the day of announcement varies significantly across the stores, suggesting high store-level heterogeneity in consumers' strategic behaviors.

Figure 12 reports each store's estimated strategic returns with bootstrapped standard errors.[21] About 1/4 of the stores have statistically significant strategic returns at $\alpha = 0.05$ (colored in blue in Figure 12). Sum of strategic returns in those stores amounts to 9,595,584 INR (about 0.14M USD). Median size is 41% of the average daily returns (9,713 INR) and the 3rd quartile is 298% (120,903 INR), which implies a notable increase in returns and the associated costs to the retailer.

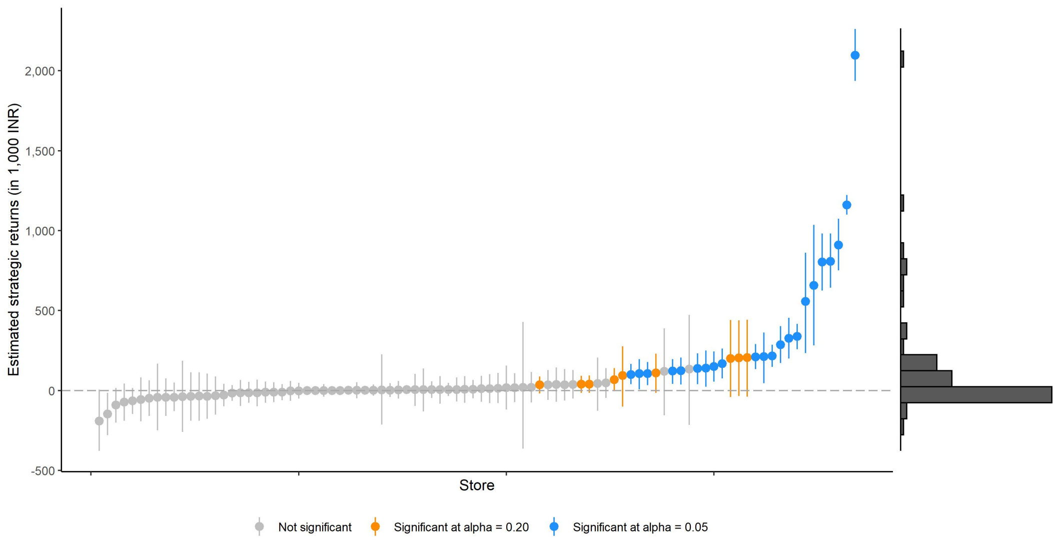


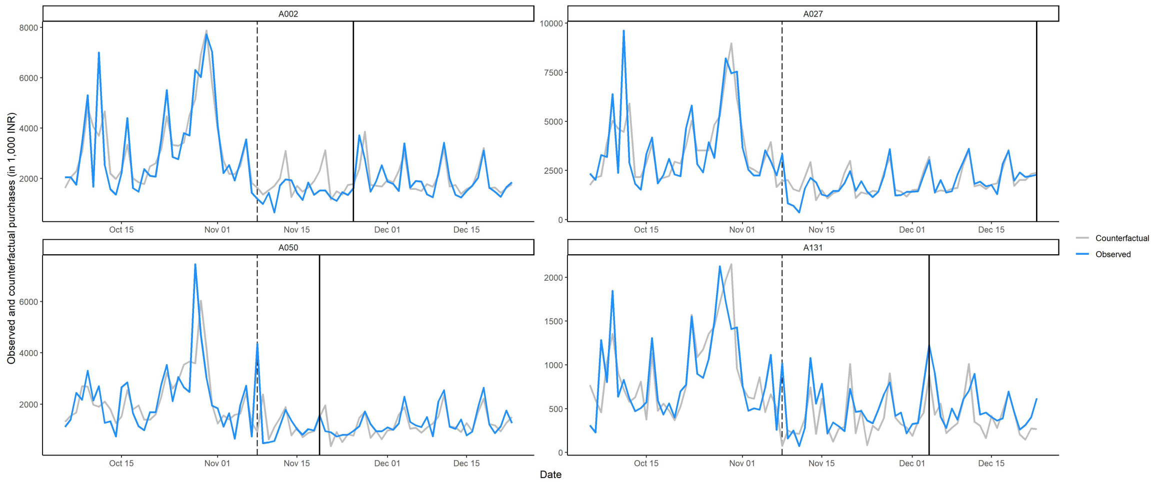

**Figure 12:** Estimated strategic returns in an ascending order with bootstrapped standard errors. Bars report 95% confidence intervals.

### 7.2 Strategic purchases

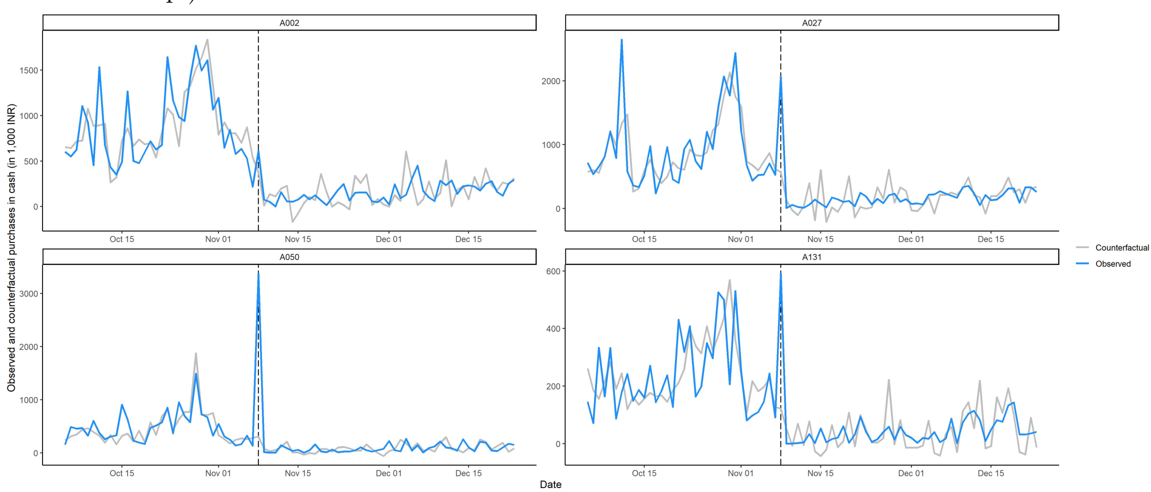
As discussed in Section 4, we separately quantify three types of strategic purchases: accelerated purchases, switching to cash, and incremental purchases.

Figure 13 collates the observed purchases with counterfactual values without strategic transactions for a sample of stores. The plots highlight high store-level heterogeneity in each type of strategic purchases. For example, Store A002 has observed daily final purchases (blue line) that are much lower than the counterfactual (gray line) for a few weeks after the policy announcement,

[21] We validate the bootstrapping method by checking that a forecasting approach using the fitted ARIMA model gives similar standard errors.




**(a)** Daily final purchases in sample stores (Solid vertical line marks the estimated end of sales dip.)




**(b)** Daily final cash purchases in sample stores

**Figure 13:** Observed and counterfactual purchases in sample stores

indicating a large amount of accelerated purchases (the top left cell of Figure 13(a)). Store A050, in contrast, does not show any suggestive pattern of purchase acceleration but has a notceable increase in cash purchases on the day of announcement, which implies a significant amount of incremental final purchases (the bottom left cell of Figure 13(b)).

Figure 14 reports each store's estimated total increase in final cash sales without decomposing them into the three sub-types. This estimate can be interpreted as an upper bound of incremental final purchases at a given store under the assumption that all the net increase in cash purchases comes from purchase expansion instead of from purchase acceleration or payment switching. 71 out of 92 stores have positive estimates of the increase in cash purchases on the day of announcement, among which 34 stores have statistically significant estimates. Median size is 87,458 INR (40% of average daily sales), which suggests that the increase is economically significant as well.

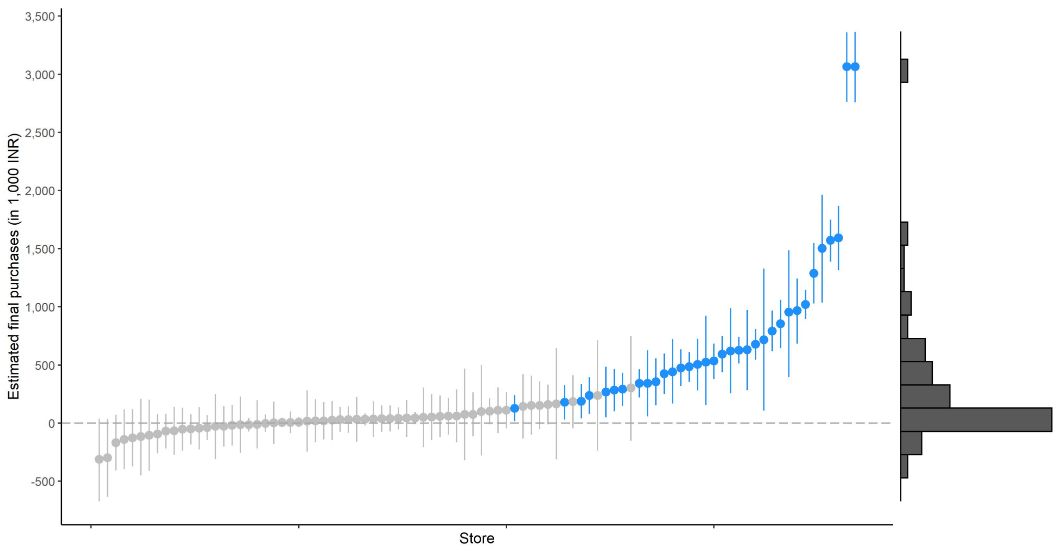



**Figure 14:** Estimated total strategic purchases ($A_s + S_s + I_s$ in Equation (10); *upper bound* of strategic purchase expansion) in an ascending order with bootstrapped standard errors. Bars report 95% confidence intervals.

**Accelerated final purchases** Figure 15 reports stores' estimated accelerated final purchases with bootstrapped standard errors.[22] Confidence intervals are wide for accelerated purchases because they are estimated as a sum of the differences between the observed daily purchases and the bootstrapped counterfactual daily purchases over a sales dip period. Given the large standard errors, there is only one store with statistically significant accelerated purchases at $\alpha = 0.05$. Accelerated purchases are significant at $\alpha = 0.20$ for 19 out of 92 stores. Median is 331,720 INR (192% of average daily final sales).

[22]We validate the bootstrapping method by checking the normality of distributions of bootstrapped estimates.

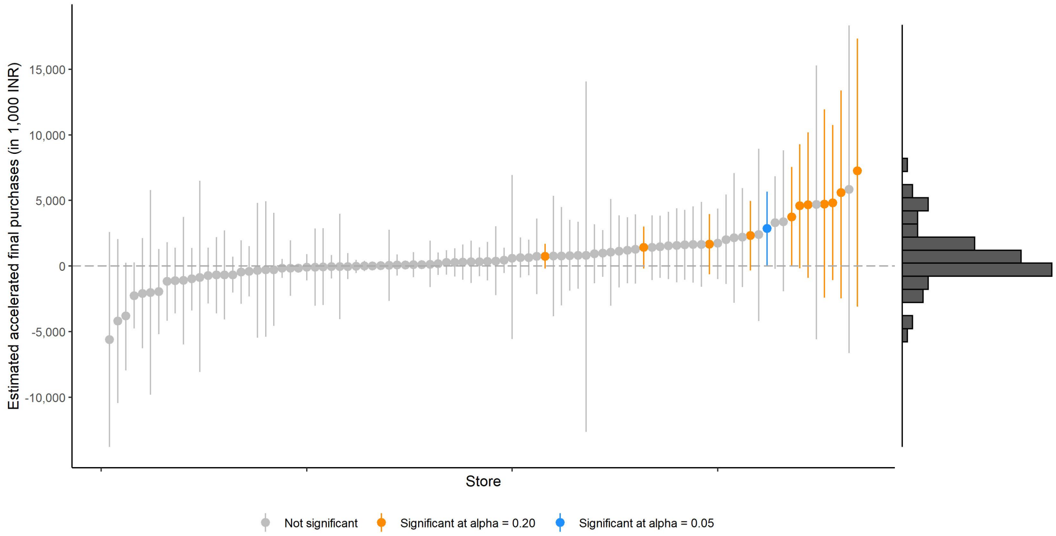



**Figure 15:** Estimated accelerated final purchases in an ascending order with bootstrapped standard errors. Bars report 95% confidence intervals.

**Switching to cash** Figure 16 shows estimated strategic choices of cash as a payment method. 14 out of 92 stores experience statistically significant switching-to-cash behavior on the day of announcement. Median size is 27,813 INR (15% of average daily final sales), which is much smaller than the size of accelerated purchases.

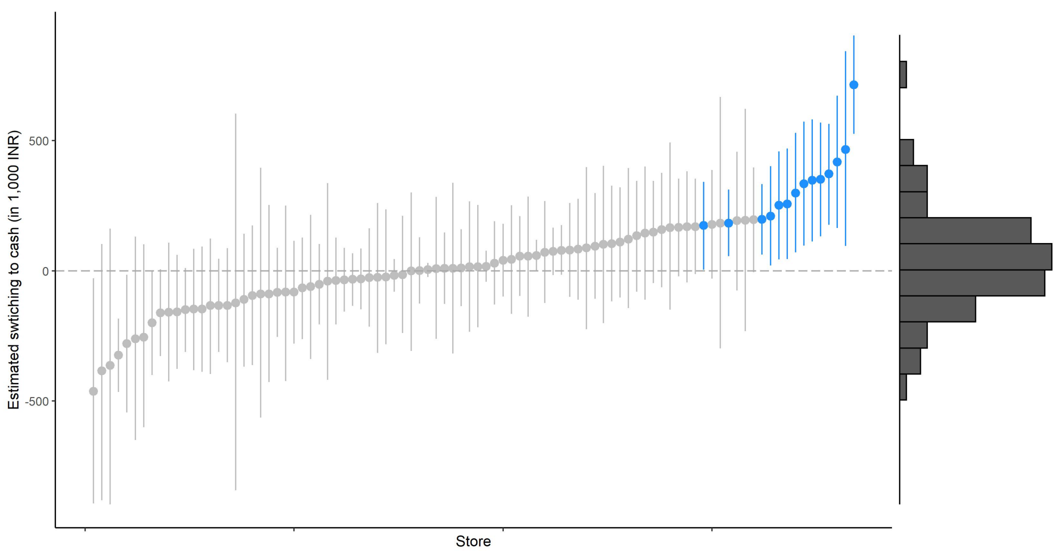



**Figure 16:** Estimated switching to cash in an ascending order with bootstrapped standard errors. Bars report 95% confidence intervals.

**Incremental final purchases** Figure 17 reports incremental final purchases, which are net of accelerated purchases and switching to cash. As accelerated purchases are large and positive for many stores, incremental final purchases become negative and statistically insignificant for most stores despite the positive increases in total cash purchases (Figure 14 vs. Figure 17). To prevent overestimation of incremental purchases, we do not subtract the estimated accelerated purchases ($A_s$) and switching to cash ($S_s$) from the observed increase in cash purchases if their value is less than 0. There are 11 stores with statistically significant incremental cash purchases, most of which do not experience any sales dip followed by the policy announcement. Median is -267,246 INR (-137% of average daily sales), which implies that on average the increase in the observed cash purchases was not large enough to compensate the experienced sales dip followed by the announcement. However, the estimates we obtain for incremental purchases are lower bounds as we attribute the entire sales dip to purchase acceleration rather than to any other market-level shocks due to demonetization.

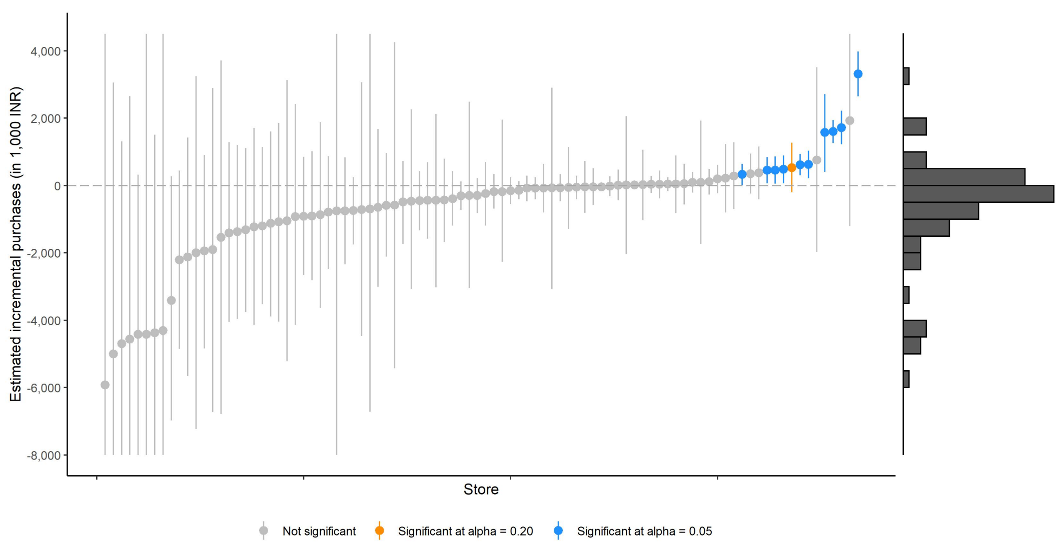



**Figure 17:** Estimated incremental final purchases (*lower bound* of strategic purchase expansion) in an ascending order with bootstrapped standard errors. Bars report 95% confidence intervals, some of which are cut for visualization.

Table 5 summarizes the distributions of estimated strategic behaviors.

**Table 5:** Distribution of strategic behaviors across stores (in 1,000 INR)

| | Min. | 1Q | Median | Mean | 3Q | Max. |
|---|---|---|---|---|---|---|
| Strategic returns | 190.66 | -5.05 | 9.71 | 111.95 | 120.90 | 2097.67 |
| Strategic purchases (Total increase in cash purchases on the day of announcement; *Upper bound*) | -311.93 | 4.28 | 84.57 | 296.96 | 426.63 | 3064.27 |
| Accelerated | -5613.35 | -159.89 | 331.72 | 726.44 | 1558.83 | 7268.93 |
| Switching to cash | -459.47 | -66.53 | 30.40 | 40.04 | 171.67 | 728.24 |
| Incremental (*Lower bound*) | -6251.46 | -1322.15 | -307.249 | -824.604 | 55.4867 | 3325.78 |

Although not conclusive, a wide dispersion in the estimated strategic consumer behavior across stores is consistent with the finding that different regions have experienced different levels of shocks due to the demonetization policy (Chodorow-Reich et al. (2019)). We investigate the source of heterogeneity in consumers' strategic purchases in the next section.

## 7.3 Source of heterogeneity in strategic consumer behavior

If the incentives for strategic purchases and returns were to circumvent or minimize the costs that were induced by the currency reform, we should expect to see a positive correlation between the size of local demonetization shock and magnitude of strategic transactions. Research has shown that some districts experienced larger shocks than others, as both the stock of demonetized notes per capita and the arrival rate of new notes varied significantly across districts (Chodorow-Reich et al. (2019)). Therefore, we can test our prediction by looking at the correlation between the estimated store-specific strategic transactions and variables that reflect local demonetization shocks.

As a proxy for demonetization shocks, we use changes in night light activity that are collected from the VIIRS DNB data (Elvidge et al. (2017)). Chodorow-Reich et al. (2019) show that night light growth, which reflects changes in GDP, is also positively correlated with local demonetization shock. The unit of observation of the night light activity is district-month. We first remove seasonality and time trends from the data by regressing log night lights per capita on district-specific linear time trends and month categorical variables. We take the log change in the de-trended night light activity between October 2016 (pre-demonetization) and November 2016 (post-demonetization) as our proxy for the local demonetization shock.

Table 6 shows the relationship between the proxied local demonetization shocks and the estimated strategic consumer behaviors. Two patterns are noticeable. First, we find that the night light change (a proxy for local demonetization shock) is positively correlated with total strategic transactions (Column (1)), especially with incremental purchases (Column (2)). This is consistent with what our model predicts; as districts with more severe demonetization shocks are likely to have larger stock of notes to be demonetized in the local economy, those districts are likely to have more households with excessive demonetized notes that they are not willing to put into the formal tax network, which leads to larger strategic transactions. Second, accelerated final purchases are negatively correlated with the proxy for demonetization shocks (Column (3)). This is also consistent with our model prediction that the main incentive for purchase acceleration is not to avoid tax-related issues but to avoid the cost of exchanging old notes to new notes. As the cost of exchange becomes zero only if the amount of old notes to be deposited is down to zero, accelerated purchases would be beneficial only for those consumers who do not own excessive cash and can use up all the old notes via purchase acceleration. These correlations do not change when we include more control variables like average rental price of the district or stores' average shares of cash transactions in daily sales before demonetization.

Our analysis gives evidence against an alternative hypothesis that heterogeneity in supply-side responses is the main source of heterogeneity in the size of strategic transactions. We explain this with two different incentives stores may have to respond strategically to the policy announcement.

First, stores may respond heterogeneously based on the anticipated *cost* of the policy shock. If a store is located in an area that experiences a large demonetization shock (because of high stock of demonetized notes per capita and/or slow arrival rate of new notes), then the store under this cost-based incentive should show *low* willingness to accept returns (as the store would also have *low* stock of legal cash notes to return) and *low* willingness to accept old notes (as the store would also face *high* cost of exchanging old notes to new notes). If this supply-side incentive creates the observed data patterns, then we should expect negative correlation between the local demonetization shock and the size of estimated strategic transactions. However, Table 6 shows the opposite pattern; the greater the local shock was, the greater the amount of strategic transactions took place.

Second, stores' different responses to the policy announcement may come from their incentives to extract profits from households. In this case, stores may encourage more strategic *purchases* in those regions where consumers are more willing to make use of soon-to-be-demonetized cash, which is consistent with what we show in Table 6. However, under this incentive, stores in regions with higher demonetization shocks should show *less* incentives to accept any strategic *returns*, resulting in a negative correlation between the size of strategic purchases and strategic returns. But this does not hold in our data; the correlation between incremental purchases and strategic returns is positive and significant ($\rho$= 0.22, p-value = 0.03). This suggests that neither strategic purchases nor returns were mainly triggered by stores' strategic responses.

In summary, the significant correlation between the proxy for local demonetization shocks and strategic consumer behaviors further supports our hypothesis that the transactions we identify are one of the ways in which households avoid the policy-induced costs by leveraging retailers as intermediaries.

**Table 6:** Correlation between per-capita night light changes (as a proxy for local demonetization shock) and strategic consumer behavior

| | *Dependent variable: (in % of average daily sales)* | | | | |
|---|---|---|---|---|---|
| | Total strategic behaviors ($I+A+S+R$) | Strategic purchases | | | Strategic returns ($R$) |
| | | Incremental purchases ($I$) | Accelerated purchases ($A$) | Switching to cash ($S$) | |
| | (1) | (2) | (3) | (4) | (5) |
| Night light change (local demonetization shock) | $1.68^{***}$ | $2.85^{***}$ | $-2.57^{**}$ | 0.11 | $0.31^{*}$ |
| | (0.41) | (0.83) | (1.19) | (0.19) | (0.16) |
| Observations | 92 | 92 | 92 | 92 | 92 |
| $R^2$ | 0.15 | 0.12 | 0.05 | 0.004 | 0.04 |
| Adjusted $R^2$ | 0.15 | 0.11 | 0.04 | $-0.01$ | 0.03 |
| F | $16.50^{***}$ | $11.75^{***}$ | $4.68^{**}$ | 0.32 | $3.60^{*}$ |

*Note:* $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01

# 8 Net impact of strategic consumer behavior

As discussed in Section 3.2, different types of strategic consumer behavior have differential impacts on store profits and policy outcomes (Table 3). Using the estimated strategic actions, we compute the net impact of such actions on store revenues and policy outcomes.

## 8.1 Impact on retail revenues

Table 7 reports the impact of strategic consumer behaviors on retail revenues net of increased return costs at the store level. $x$ represents the assumed size of return costs as a share of transaction price. Table 7(a) shows the lower bounds of the net impact, in which the net impact is calculated as (Incremental final purchases $-$ $x\times$ Strategic returns). Table 7(b) shows the upper bounds, which is calculated as (Total increase in cash purchases $-x\times$ Strategic returns).[23]

Even in the most conservative case with the highest possible return cost ($x = 1$, the last row of

[23] This specification models all costs related to returns (e.g., repackaging costs, costs related to product damages, inventory costs) to be proportional to transaction prices and not to exceed transaction prices. This may introduce an upward bias to our profit analysis if inventory costs increase in the number of product returns in a non-linear way or increase above retail prices. We do not model incremental stock-out costs because most strategic purchases are on high-ticket items that are rarely stored in shops for immediate sales.

Table 7(a)), 1/4 of the stores benefit from strategic consumer behaviors; the store with the highest net revenue gains more than 1.5 million INR (21,000 USD) due to the households responding to the demonetization policy. If we assume that the increase in cash purchases is driven solely by purchase expansion rather than purchase acceleration, more than 3/4 of the stores experience net revenue increases due to strategic consumers.

**Table 7:** Net impact of strategic consumer behaviors on store revenues (in 1,000 INR)

(a) Lower bound of the net impact = Incremental final purchases $-$ $x\times$ Strategic returns

| Return cost | Min. | 1Q | Median | Mean | 3Q | Max. |
|---|---|---|---|---|---|---|
| $x = 0.1$ | -6271.99 | -1321.16 | -300.22 | -835.80 | 58.63 | 2983.83 |
| $x = 0.3$ | -6313.05 | -1319.18 | -287.19 | -858.19 | 40.05 | 2696.48 |
| $x = 0.5$ | -6354.1 | -1317.2 | -287.6 | -880.6 | 39.8 | 2276.9 |
| $x = 1$ | -6456.76 | -1312.26 | -404.79 | -936.55 | 30.14 | 1545.12 |

(b) Upper bound of the net impact = Total increase in cash purchases $-$ $x\times$ Strategic returns

| Return cost | Min. | 1Q | Median | Mean | 3Q | Max. |
|---|---|---|---|---|---|---|
| $x = 0.1$ | -325.35 | 4.27 | 75.85 | 285.76 | 362.15 | 3116.01 |
| $x = 0.3$ | -352.18 | 0.88 | 74.80 | 263.37 | 318.84 | 2822.94 |
| $x = 0.5$ | -379.01 | -12.06 | 64.49 | 240.98 | 299.62 | 2662.04 |
| $x = 1$ | -735.33 | -38.18 | 74.44 | 185.00 | 262.11 | 2259.81 |

At the retail chain level, total strategic purchases (identified as total increase in cash purchases on the day of announcement) dominates the size of total strategic returns (Column (1) of Table 8, first and second row). Even when we use the lower bound of strategic purchases (Table 8, last row) to assess the net impact at the chain level, the size of strategic returns is almost equal the lower bound of incremental purchases. Under the assumption that the retailer's cost associated with product returns is not greater than the transaction prices, this suggests that there is a net positive revenue at the chain level.[24]

[24]The assumption that return costs do not exceed transaction prices is more plausible as most returns were among high-ticket items (Figure 3).

### 8.2 Impact on policy outcome

To analyze how much cash stays outside the formal tax network because of strategic transactions by consumers, we first sum the amount of cash from statistically significant strategic returns and incremental final purchases across the stores (Column (3) and (5) in Table 8). About 19.3 million INR are not deposited to bank accounts (0.28 million USD) via this route, which goes up to 36.1 million INR (0.54 million USD) if we attribute the entire increase in cash sales to purchase expansion instead of purchase acceleration.

To gauge the impact of strategic consumer transactions on the policy outcome at the country level, we scale up the estimate based on the ratio of the chain's yearly sales to the retail market size in India.[25] In 2016, total sales of the chain is about 0.02% of the entire retail market size. If other retail stores on average offer leeway to households in a similar manner that the chain does, up to 96.5 billion INR (= 19.3 million INR / 0.02% ; 1.44 billion USD) of household cash is estimated as avoiding the government tax system despite the demonetization policy. If we use the less (but still) conservative estimate of strategic transactions, the size of cash notes avoiding the tax net goes up to 181 billion INR (= 36.1 million INR / 0.02%; 2.7 billion USD), which is 1.2% of the entire 500 and 1,000 INR notes being circulated before demonetization.[26]

The impact of strategic transactions is still significant when we take into account an increase in the government's tax revenue through sales tax. For more precise evaluation of the policy, we do a back-of-envelope calculation on tax revenues using the following formula:

[25] Retail market size across India from 2011 to 2018, with estimates until 2026 (in billion U.S. dollars), Statista, Oct 16, 2020.

[26] Reserve Bank of India Annual Report 2015-2016.

$$
\begin{aligned}
\text{Tax revenue loss} =& (\text{Income tax} + \text{Tax evasion penalty}) - \text{Sales tax} \\
=& (0.3 + 2.0) \times \text{Strategic purchases} - 0.11 \times \text{Strategic Purchases} \\
=& 2.19 \times \text{Strategic purchases} \\
& \in [211.3 \text{ billion INR}, 396.4 \text{ billion INR}] \\
& (\approx [3.2 \text{ billion USD}, 5.9 \text{ billion USD}])
\end{aligned} \tag{11}
$$

where 11% is sales tax, 30% is the tax rate for households with more than 1,000,000 INR annual income (≈ 15,000 USD), and 200% is the penalty for intentional tax evasion.[27] As the calculation suggests, the loss in tax revenues could be almost 400 billion INR (6 billion USD) because of the sizeable gap between sales tax and income-related tax revenues. This gap also explains households' incentives to make strategic purchases with cash instead of depositing it into their bank accounts.

Note that the total estimated impact is still a strictly conservative estimate for two additional reasons. First, even more cash would have survived through strategic transactions in markets with much higher-ticket items like luxury jewelries or even real estates. Second, media reports suggest small businesses responded more flexibly to strategic consumers, encouraging incremental purchases with backdated receipts and charging higher prices for items transacted with demonetized notes.[28]. Our estimates are from transactions at a national retail chain with much less flexibility on supply-side strategic responses, which makes our policy evaluation likely to be underestimated.

In summary, strategic transactions are estimated to be sizable enough to affect one of the key policy goals in the case of demonetization in India. This finding, combined with the analysis of net

[27] Income Tax Slab Rates & Deductions for FY 2016-17 & 2017-2018, HDFC Life.
"What is Tax Evasion And What Are The Penalties For Tax Evasion In India?", Kotak Life.

[28] "Jewellers issue backdated invoices to clients," The Economic Times, Nov. 10, 2016.

impact on retail revenues, sheds light on potential economic significance of strategic transactions by consumers on policy aims as well as on retail performance.

**Table 8:** Impact on the policy outcome: Aggregate size of strategic transactions by type

| | | $\alpha = 0.05$ | | $\alpha = 0.20$ | |
|---|---|---|---|---|---|
| | Sum across all stores* (1) | # Stores with significant estimates (2) | Sum of significant estimates* (3) | # Stores with significant estimates (4) | Sum of significant estimates* (5) |
| Strategic returns | 10299.46 | 22 | 9735.73 | 31 | 10728.49 |
| Strategic purchases (Total increase in cash purchases on the day of announcement; *Upper bound*) | 27319.82 | 34 | 26414.19 | 42 | 27572.39 |
| Accelerated | 66832.02 | 1 | 2855.97 | 19 | 58109.38 |
| Switching to cash | 3683.85 | 3 | 1520.26 | 15 | 4809.43 |
| Incremental (*Lower bound*) | -75863.54 | 9 | 9604.53 | 10 | 10133.51 |

*: in 1,000 INR

# 9 Conclusion

Using transaction-level data from a large retail chain selling big ticket items in India, we empirically document how households as consumers avoid or minimize policy-induced costs via strategic transactions at retail stores. In the context of demonetization in India, such strategic consumer behaviors resulted in a significant impact that ran counter to the policy aim while benefiting both households the retail chain. Our finding underscores the importance of careful policy design that incorporates the possibility of unintended consequences due to the behavior of consumers at the retail level. Our findings also highlight a new role for retailers in absorbing and responding to macro-level shocks. We observe that, under the currency reform, retailers (partly) take on the function of financial institutions by accepting soon-to-be demonetized bills as well as distributing legal notes in their local economies.

The paper has several limitations. First, our empirical context is a large-scale demonetization policy, whose rare occurrence restricts the generalizability of our finding to the contexts outside the currency reform policy. However, fighting against illicit financial flows and transitioning to a cashless society are major interests of many developing economies (OECD (2014), World Bank Group (2016)), and government-led currency reform is one of the tools that have been widely used to achieve such goals (Staehr (2015)). Therefore, consumer behaviors and unintended consequences studied in the paper have broader implications to policy makers and retailers whose local economy is undergoing the initiatives to raise economic transparency. Second, strategic behaviors of consumers can vary across the types of product categories depending on buyer and retailer side considerations. Our analysis should therefore be seen as suggestive rather than representative of the larger retailer landscape for durable goods. Third, methodologically, our decomposition of strategic purchases requires us to infer the duration of the sales dip from the data. To the extent that supplementary information may be available in other product categories that allow researchers to pin down the various components, better estimates of the three elements of strategic purchases that we discuss may be possible.

Much anecdotal evidence and popular press reporting have suggested possible strategic behavior by consumers during the period of India's demonetization. However, systematic evidence of such behavior at the consumer level has been scarce. We hope our analysis sheds more light on the micro-level consequences of this macro-level intervention. More broadly, we hope to call for more attention to causes and effects of collective strategic actions by consumers in the presence of market-level shocks.

# References

Adjerid, I., Acquisti, A., Telang, R., Padman, R., & Adler-Milstein, J. (2016, apr). The impact of privacy regulation and technology incentives: The case of health information exchanges. *Management Science*, *62*(4), 1042–1063. doi: 10.1287/mnsc.2015.2194

Anderson, E., Fong, N. M., Simester, D. I., & Tucker, C. E. (2010, apr). How sales taxes affect customer and firm behavior: The role of search on the internet. *Journal of Marketing Research*, *47*(2), 229–239. doi: 10.1509/jmkr.47.2.229

Anderson, E., & Simester, D. (2008). Price stickiness and customer antagonism. *SSRN Electronic Journal*. doi: 10.2139/ssrn.1273647

Anderson, E. T., Hansen, K., & Simester, D. (2009, may). The option value of returns: Theory and empirical evidence. , *28*(3), 405–423. doi: 10.1287/mksc.1080.0430

Aridor, G., Che, Y.-K., Nelson, W., & Salz, T. (2020). The economic consequences of data privacy regulation: Empirical evidence from GDPR. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3522845

Aviv, Y., & Vulcano, G. (2012). *Dynamic list pricing.* Oxford University Press. doi: 10.1093/oxfordhb/9780199543175.013.0023

Aviv, Y., Wei, M. M., & Zhang, F. (2019). Responsive pricing of fashion products: The effects of demand learning and strategic consumer behavior. *Management Science*, *65*(7), 2982-3000. Retrieved from `https://doi.org/10.1287/mnsc.2018.3114` doi: 10.1287/mnsc.2018.3114

Biswas, S., Chintagunta, P. K., & Dhar, S. K. (2019). Income and wealth effects on consumer packaged goods purchases. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3503602

Bollinger, B., Leslie, P., & Sorensen, A. (2011, feb). Calorie posting in chain restaurants. *American Economic Journal: Economic Policy*, *3*(1), 91–128. doi: 10.1257/pol.3.1.91

Bollinger, B., & Sexton, S. (2017). Local excise taxes, sticky prices, and spillovers: Evidence from berkeley's soda tax. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3087966

Cachon, G. P., & Swinney, R. (2009). Purchasing, pricing, and quick response in the presence of strategic consumers. *Management Science*, *55*(3), 497-511. Retrieved from `https://doi.org/10.1287/mnsc.1080.0948` doi: 10.1287/mnsc.1080.0948

Chandy, R. K., Johar, G. V., Moorman, C., & Roberts, J. H. (Eds.). (2021, apr). Special issue: Better marketing for a better world. *Journal of Marketing*, *85*(3). Retrieved from `https://journals.sagepub.com/toc/jmx/85/3`

Chodorow-Reich, G., Gopinath, G., Mishra, P., & Narayanan, A. (2019, 09). Cash and the Economy: Evidence from India's Demonetization*. *The Quarterly Journal of Economics*, *135*(1), 57-103. Retrieved from `https://doi.org/10.1093/qje/qjz027` doi: 10.1093/qje/qjz027

Cohen, M. A., & Rysman, M. (2013). Payment choice with consumer panel data. *SSRN Electronic Journal*. doi: 10.2139/ssrn.2308121

Cohen, M. C., Lobel, R., & Perakis, G. (2016, may). The impact of demand uncertainty on consumer subsidies for green technology adoption. *Management Science*, *62*(5), 1235–1258. doi: 10.1287/mnsc.2015.2173

Coughlan, A., Anderson, E., Stern, L., & El-Ansary, A. (2006). *Marketing channels* (7th ed.). Prentice Hall.

Davies, J. (2019). *After gdpr, the new york times cut off ad exchanges in europe and kept growing ad revenue.* Digiday.

Davis, B., Grewal, D., & Hamilton, S. (2021, oct). The future of marketing analytics and public policy. , *40*(4), 447–452. doi: 10.1177/07439156211042372

Drechsler, I., Savov, A., & Schnabl, P. (2017, may). The deposits channel of monetary policy. *The Quarterly Journal of Economics*, *132*(4), 1819–1876. doi: 10.1093/qje/qjx019

Dubé, J.-P., Hitsch, G. J., & Rossi, P. E. (2018, jan). Income and wealth effects on private-label demand: Evidence from the great recession. *Marketing Science*, *37*(1), 22–53. doi: 10.1287/mksc.2017.1047

Economic survey 2019-20. (2020, January). In (Vol. 1, p. 67-98). Government of India Ministry of Finance Department of Economic Affairs Economic Division.

Elvidge, C. D., Baugh, K., Zhizhin, M., Hsu, F. C., & Ghosh, T. (2017, jun). VIIRS night-time lights. *International Journal of Remote Sensing*, *38*(21), 5860–5879. doi: 10.1080/01431161.2017.1342050

Fletcher, J. M., Frisvold, D. E., & Tefft, N. (2010, dec). The effects of soft drink taxes on child and adolescent consumption and weight outcomes. *Journal of Public Economics*, *94*(11-12), 967–974. doi: 10.1016/j.jpubeco.2010.09.005

Haggin, P., & Higgins, T. (2021, March). Apple's move to block user tracking spawns new digital ad strategies. *The Wall Street Journal*. Retrieved from `https://www.wsj.com/articles/apples-move-to-block-user-tracking-spawns-new-digital-ad-strategies-11616751001?st=dcdz2d5c6emjmbq&reflink=desktopwebshare_permalink`

Hall, T. (2014). *Aftermath: The unintended consequences of public policies.* Cato Institute. Retrieved from `https://books.google.com/books?id=hAC5ngEACAAJ`

Hartmann, W. R. (2006, oct). Intertemporal effects of consumption and their implications for demand elasticity estimates. *Quantitative Marketing and Economics*, *4*(4), 325–349. doi: 10.1007/s11129-006-9012-2

He, C., Ozturk, O. C., Gu, C., & Silva-Risso, J. M. (2021, jan). The end of the express road for hybrid vehicles: Can governments' green product incentives backfire? *Marketing Science*, *40*(1), 80–100. doi: 10.1287/mksc.2020.1239

Hendel, I., & Nevo, A. (2003, dec). The post-promotion dip puzzle: What do the data have to say? *Quantitative Marketing and Economics*, *1*(4), 409–424. doi: 10.1023/b:qmec.0000004844.32036.5a

Hoffmann, P., Langfield, S., Pierobon, F., & Vuillemey, G. (2018, nov). Who bears interest rate risk? *The Review of Financial Studies*, *32*(8), 2921–2954. doi: 10.1093/rfs/hhy113

Hu, P., Shum, S., & Yu, M. (2016). Joint inventory and markdown management for perishable goods with strategic consumer behavior. *Operations Research*, *64*(1), 118-134. Retrieved from `https://doi.org/10.1287/opre.2015.1439` doi: 10.1287/opre.2015.1439

Kleven, H. J. (2016, oct). Bunching. *Annual Review of Economics*, *8*(1), 435–464. doi: 10.1146/annurev-economics-080315-015234

Kleven, H. J., & Waseem, M. (2013, apr). Using notches to uncover optimization frictions and structural elasticities: Theory and evidence from pakistan. *The Quarterly Journal of Economics*, *128*(2), 669–723. doi: 10.1093/qje/qjt004

Kostov, N., & Schechner, S. (2019). Gdpr has been a boon for google and facebook. *Wall Street Journal, June*, *17*.

Koulayev, S., Rysman, M., Schuh, S., & Stavins, J. (2016). Explaining adoption and use of payment instruments by us consumers. *The RAND Journal of Economics*, *47*(2), 293-325. Retrieved from https://onlinelibrary.wiley.com/doi/abs/10.1111/1756-2171.12129 doi: 10.1111/1756-2171.12129

Lahiri, A. (2020, feb). The great indian demonetization. *Journal of Economic Perspectives*, *34*(1), 55–74. doi: 10.1257/jep.34.1.55

Lahiri, S. N. (2003). *Resampling methods for dependent data*. Springer New York. doi: 10.1007/978-1-4757-3803-2

Lin, T. (2019). Valuing intrinsic and instrumental preferences for privacy. *SSRN Electronic Journal*. doi: 10.2139/ssrn.3406412

Maggio, M. D., Kermani, A., Keys, B. J., Piskorski, T., Ramcharan, R., Seru, A., & Yao, V. (2017, nov). Interest rate pass-through: Mortgage rates, household consumption, and voluntary deleveraging. *American Economic Review*, *107*(11), 3550–3588. doi: 10.1257/aer.20141313

Mantin, B., & Rubin, E. (2016). Fare prediction websites and transaction prices: Empirical evidence from the airline industry. *Marketing Science*, *35*(4), 640-655. Retrieved from https://doi.org/10.1287/mksc.2015.0965 doi: 10.1287/mksc.2015.0965

Nair, H. (2007, aug). Intertemporal price discrimination with forward-looking consumers: Application to the US market for console video-games. *Quantitative Marketing and Economics*, *5*(3), 239–292. doi: 10.1007/s11129-007-9026-4

OECD. (2014). *Illicit financial flows from developing countries: Measuring oecd responses*. Author.

Petersen, J. A., & Kumar, V. (2015, apr). Perceived risk, product returns, and optimal resource allocation: Evidence from a field experiment. , *52*(2), 268–285. doi: 10.1509/jmr.14.0174

Rao, A., & Wang, E. (2017, dec). Demand for "healthy" products: False claims and FTC regulation. *Journal of Marketing Research*, *54*(6), 968–989. doi: 10.1509/jmr.15.0398

Reece, W. S., & Zieschang, K. D. (1985, mar). Consistent estimation of the impact of tax deductibility on the level of charitable contributions. *Econometrica*, *53*(2), 271. doi: 10.2307/1911236

Robertson, T. S., Hamilton, R., & Jap, S. D. (2020, jun). Many (un)happy returns? the changing nature of retail product returns and future research directions. *Journal of Retailing*, *96*(2), 172–177. doi: 10.1016/j.jretai.2020.04.001

Saez, E. (2010, aug). Do taxpayers bunch at kink points? *American Economic Journal: Economic Policy*, *2*(3), 180–212. doi: 10.1257/pol.2.3.180

Seiler, S., Tuchman, A., & Yao, S. (2020, dec). The impact of soda taxes: Pass-through, tax avoidance, and nutritional effects. *Journal of Marketing Research*, *58*(1), 22–49. doi: 10.1177/0022243720969401

Song, I., & Chintagunta, P. K. (2003, dec). A micromodel of new product adoption with heterogeneous and forward-looking consumers: Application to the digital camera category. *Quantitative Marketing and Economics*, *1*(4), 371–407. doi: 10.1023/b:qmec.0000004843.41279.f3

Soysal, G. P., & Krishnamurthi, L. (2012, mar). Demand dynamics in the seasonal goods industry: An empirical analysis. *Marketing Science*, *31*(2), 293–316. doi: 10.1287/mksc.1110.0693

Staehr, K. (2015). Currency reforms in emerging-market and transition economies. In *Palgrave dictionary of emerging markets and transition economics* (pp. 28–38). Palgrave Macmillan UK. doi: 10.1007/978-1-137-37138-6_3

Wadhwa, S. (2019). Impact of demonetization on household consumption in india..

Wirl, F. (1996). The design of optimal conservation programs by electric utilities considering strategic consumer behavior. *Management Science*, *42*(3), 404-414. Retrieved from https://doi.org/10.1287/mnsc.42.3.404 doi: 10.1287/mnsc.42.3.404

World Bank Group. (2016). Small retailers transact $19 trillion in cash annually, new world economic forum and world bank group study shows. *The World Bank*. Retrieved 2016-06-27, from https://www.worldbank.org/en/news/press-release/2016/06/27/small-retailers-transact-19-trillion-in-cash-annually-new-world-economic-forum-and-world-bank-group-study-shows

Xiao, P., Xiao, R., Liang, Y. S., Chen, X. J., & Lu, W. (2020, jul). The effects of a government's subsidy program: Accessibility beyond affordability. *Management Science*, *66*(7), 3211–3233. doi: 10.1287/mnsc.2019.3334

Xue, M., Hitt, L. M., & Chen, P.-y. (2011). Determinants and outcomes of internet banking adoption. *Management Science*, *57*(2), 291-307. Retrieved from https://doi.org/10.1287/mnsc.1100.1187 doi: 10.1287/mnsc.1100.1187

Yang, B., & Ching, A. T. (2014). Dynamics of consumer adoption of financial innovation: The case of atm cards. *Management Science*, *60*(4), 903-922. Retrieved from https://doi.org/10.1287/mnsc.2013.1792 doi: 10.1287/mnsc.2013.1792

Yu, M., Debo, L., & Kapuscinski, R. (2016). Strategic waiting for consumer-generated quality information: Dynamic pricing of new experience goods. *Management Science*, *62*(2), 410-435. Retrieved from https://doi.org/10.1287/mnsc.2014.2134 doi: 10.1287/mnsc.2014.2134

# Appendix

## A.1 A model of consumers' strategic responses to the policy

With model-free evidence in hand, we introduce a simplified model to explore how households' different incentives to minimize the shock from demonetization generate such observed increases in returns and purchases. We do not sketch any strategic responses of retailers in this model as the abruptness of the policy enactment allows us to assume that there is no overnight response by the retail chain, which we also confirm reviewing news articles. Future work may extend the framework and incorporate the supply side decisions to understand an equilibrium outcome when both households and firms are expected to react simultaneously.

Before the currency reform policy, household $i$ has the following utility function attached to their cash income:

$$\begin{aligned} u_i &= U(z_i - T(z_i')) \\ &= U(z_i - T(z_i - b_i)), \quad 0 \leq b_i \leq z_i \end{aligned} \tag{A.0.1}$$

where $z_i$ is before-tax earnings in cash that is saved in soon-to-be demonetized notes (500 and 1000 INR notes), $z_i' = z_i - b_i$ is *reported* taxable income in cash, and $T(\cdot)$ is a tax function which is monotonically increasing. For simplicity, we define the tax function $T$ to be the following:

$$T(z) = (1-t)(z - z^*)\mathbb{1}\{z > z^*\} \tag{A.0.2}$$

where $z^*$ is the earning threshold above which a marginal tax rate $t$ is applied. Under this tax system, households whose earnings in cash are greater than $z^*$ can reduce the amount of tax paid by reporting their income to be smaller. We assume that $U(\cdot)$ is linear in after-tax income $z_i - T(z_i')$.

The demonetization policy changes the utility function in several ways. First, it puts a restriction on how much households can shade their income in cash by forcing them to deposit or exchange the demonetized cash notes at the banks. In the utility function, this is reflected as $b_i = 0$ after demonetization. Second, it penalizes those households that have been evading taxes, i.e., whose $b_i$ has been greater than 0. This introduces a new term $P(\cdot)$ in the utility function after demonetization, which is the tax penalty as a function of the size of avoided tax $(T(z_i) - T(z_i - b_i))$. We assume the following functional form for the tax penalty:

$$\begin{aligned} P_i &= (\pi_o + \pi_1(T(z_i) - T(z_i - b_i))) \cdot \mathbb{1}\{b_i > 0\} \\ &= (\pi_o + \pi_1 t b_i) \cdot \mathbb{1}\{b_i > 0\} \qquad (\because \text{Equation (A.0.2)}) \end{aligned} \tag{A.0.3}$$

where $\pi_0$ denotes a flat fee that anyone has to pay if their amount of tax evasion $(tb_i)$ is greater than 0. Third, due to the imminent cash shortage and the increased traffic at the banks, the policy creates a cost related to exchanging or depositing the cash notes at the banks (e.g., waiting in line for hours). We assume that this cost has to be paid once for any household who has positive amount of demonetized cash. We specify the depositing cost $D$ to be

$$D_i = \begin{cases} D & \text{if holdings of cash to be demonetized} > 0 \\ 0 & \text{if holdings of cash to be demonetized} = 0 \end{cases} \tag{A.0.4}$$

Combining these components, the new utility function is

$$\begin{aligned} u_i^{Post} &= U\left(z_i - T(z_i) - P(tb_i) - D(z_i)\right) \\ &= U\left(\underbrace{z_i - T(z_i) - (\pi_0 + \pi_1 tb_i)\cdot \mathbb{1}\{b_i > 0\}}_{\text{New budget set}} - \underbrace{D \cdot \mathbb{1}\{z_i > 0\}}_{\text{Depositing cost}}\right) \end{aligned} \tag{A.0.5}$$

where $tb_i$ is the total amount of avoided tax (following Equation (A.0.2)).

**1) Strategic returns** Households can save on tax penalty by making purchases with soon-to-be demonetized cash notes and returning the items to receive legal notes from the retailer. For some households whose before-tax income in demonetized cash ($z_i$) is not large, such strategic returns can even save the depositing cost by converting all $z_i$ to legal notes.

Suppose that $R_i$ is the amount of purchases household $i$ makes with old notes that are later returned for legal notes. Then, $i$'s utility function with strategic returns becomes

$$u_i^{Return} = U\left(z_i \underbrace{-R_i + R_i}_{\substack{\text{Purchases followed}\\ \text{by returns}}} - \underbrace{T(z_i - R_i)}_{\text{Savings in tax}} - \underbrace{(\pi_0 + \pi_1 t(b_i - R_i))\cdot \mathbb{1}\{b_i - R_i > 0\}}_{\text{Savings in penalty}} - \underbrace{D \cdot \mathbb{1}\{z_i - R_i > 0\}}_{\text{Savings in depositing cost}}\right) \tag{A.0.6}$$

$$\geq u_i^{Post} = U\left(z_i - T(z_i) - (\pi_0 + \pi_1 tb_i)\cdot \mathbb{1}\{b_i > 0\} - D \cdot \mathbb{1}\{z_i > 0\}\right).$$

$R_i$, the amount of money that is converted to legal notes via strategic returns, does not have to be deposited to bank accounts and thus can stay outside the formal tax network. As illustrated in Equation (A.0.6), this saves household income in three different ways: 1) by reducing the amount of tax to be collected, 2) by reducing the penalty attached to former tax evasion, and 3) by removing the depositing cost if all demonetized cash can be converted to legal notes this way. Here, we do not assume any frictions or cost associated with the return activity itself, including the cost of multiple store visits.

Although strategic returns would give the highest utility to households given the policy, a strict return policy does not always guarantee that such returns can take place. Although any purchased items can be returned in 7 days if there are any issues with the products according to the store managers we contacted, anecdotal evidence suggests that the refund option for simple change of mind is rarely available. Also, even the most generous refund policy in the market still requires certain conditions to be met like intact packaging. This implies that, among people who made purchases on the day of announcement before the policy information became public, only those who did not open the package could attempt to return the purchased items which was not always successful. Even those people who made purchases after the policy announcement before the effective date purely for strategic purposes had to go through the stringent return process that not everyone could complete.

**2) Incremental final purchases** For households who have evaded a large amount of tax before the policy, it can still be beneficial to convert soon-to-be demonetized notes to physical products even if the option of return is not available, since such purchases lower post-policy tax and tax penalty. Household $i$'s utility with these strategic final purchases is

$$u_i^{IncPurchase} = U\left(z_i - C_i - \underbrace{T(z_i - C_i)}_{\text{Savings in tax}} - \underbrace{(\pi_0 + \pi_1 t(b_i - C_i)) \cdot \mathbb{1}\{b_i - C_i > 0\}}_{\text{Savings in penalty}} - \underbrace{D \cdot \mathbb{1}\{z_i - C_i > 0\}}_{\text{Savings in depositing cost}}\right) \tag{A.0.7}$$

$$\geq u_i^{Post} = U\left(z_i - T(z_i) - (\pi_0 + \pi_1 t b_i) \cdot \mathbb{1}\{b_i > 0\} - D \cdot \mathbb{1}\{z_i > 0\}\right)$$
$$\text{if } C_i \leq T(z_i) - T(z_i - C_i) + \pi_1 C_i \mathbb{1}\{b_i > 0\} + D_i \mathbb{1}\{z_i - C_i \leq 0\}$$

where $C_i$ is the amount of strategic purchases made with demonetized cash notes. The inequalities imply that it is beneficial for $i$ to discard $C_i$ as long as $C_i$ is less than the savings $i$ gets from a lower tax penalty and zero depositing cost. This is consistent with households' abandonment of demonetized cash without depositing it, which is documented in press reports:

> "Some have thrown in the towel, rather than risking an investigation into their taxes, filling pillowcases and paper bags with the old currency and dumping them in the trash. Notes of 1,000 rupees, the equivalent of about $15, have been spotted floating down the Ganges River."
>
> "Indians Rush Frantically to Launder Their 'Black Money,'" The New York Times, Nov. 20, 2016.

Figure 18 illustrates graphically how the policy can trigger such strategic purchases or cash disposal.[29] Before the policy, after-tax income of households whose before-tax earnings are greater

[29] We closely follow an illustrative graph in Kleven & Waseem (2013) to demonstrate our context.

than $z^*$ should follow the tax schedule represented as line $B$ in the graph ($Y = z^* + (1-t)(z - z^*)\mathbb{1}\{z > z^*\}$). Conditional on tax evasion behavior, the actual after-tax income stays along the line $A$ ($Y = z$) as households under-report their income to be $z' = z^*$. After the policy enactment, the new budget set becomes $Y = z^* + (1-t)(z - z^*)\mathbb{1}\{z > z^*\} - (\pi_o + \pi_1 t b_i) \cdot \mathbb{1}\{b_i > 0\}$ (Equation (A.0.5)), which is represented as line C. The policy introduces a discrete shift in the budget set at $z^*$ for tax-evading households due to the flat fee component of the tax penalty ($\pi_0$ in Equation (A.0.3)). The slope of the after-policy budget above the threshold $z^*$ (line $C$) is flatter than the slope of the full tax schedule (line B) because of the tax penalty proportional to the avoided tax amount ($\pi_1$ in Equation (A.0.3)).

These shifts in the income schedule introduced by the policy explain why some households are willing to make extra purchases with cash or to even dispose cash as news articles report. After the policy is enforced, because of the higher full tax as well as the penalty associated with previous tax evasion, there is a region of before-tax income $[z^*, z^I)$ that is strictly dominated by $z^*$. In other words, within $[z^*, z^I)$, pre-tax income greater than $z^*$ gives a lower after-tax income than $z^*$ does. This results in behavioral responses among certain households to lower the income to be $z^*$ via strategic purchases (Figure 18(b)). The region of before-tax income that is dominated by $z^*$ increases as the flat fee component and the linear rate of tax evasion penalty becomes higher (i.e., as line C in Figure 18(a) shifts down and becomes flatter with higher $\pi_0$ and $\pi_1$).

Note that $u_i^{IncPurchase}$ in Equation (A.0.7) assumes that that 1) the products purchased do not provide any consumption utility, and 2) they cannot be resold in the second-hand market. These assumptions make purchase activities similar to cash discarding, which provides the lower bound of the utility from strategic purchases.

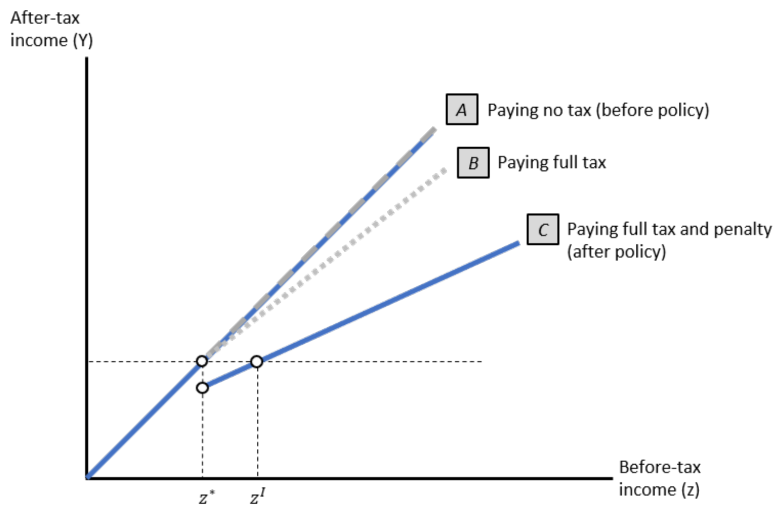
Incremental purchases in response to the policy can be larger when reselling purchased items is allowed. Suppose that households can resell the purchased items $C_i$ in the second-hand market at a discounted price, $\theta C_i$, where $0 < \theta < 1$. Then, household $i$'s utility from strategic purchases and reselling becomes

$$u_i^{IncPurchase'} = U\left( z_i \underbrace{-C_i + \theta C_i}_{\substack{\text{Part of value}\\ \text{recouped}\\ \text{via reselling}}} + \underbrace{T(z_i - C_i)}_{\text{Savings in tax}} - \underbrace{(\pi_0 + \pi_1 t(b_i - C_i)) \cdot \mathbb{1}\{b_i - C_i > 0\}}_{\text{Savings in penalty}} - \underbrace{D \cdot \mathbb{1}\{z_i - C_i > 0\}}_{\text{Savings in depositing cost}} \right) \tag{A.0.8}$$

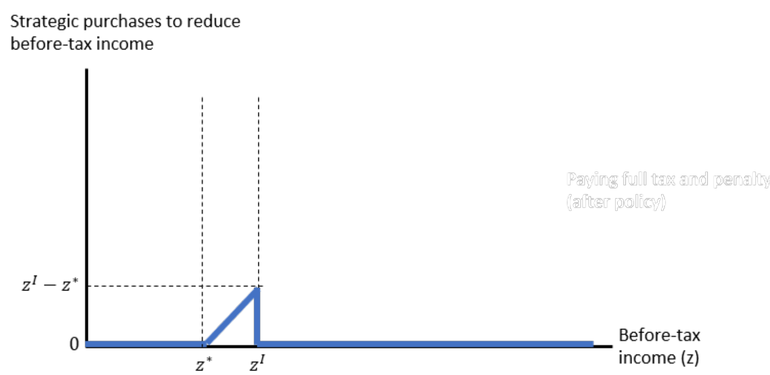
$$\geq u_i^{Post} = U\left(z_i - T(z_i) - (\pi_0 + \pi_1 t b_i) \cdot \mathbb{1}\{b_i > 0\} - D \cdot \mathbb{1}\{z_i > 0\}\right)$$

$$\text{if} \quad (1-\theta)C_i \leq T(z_i) - T(z_i - C_i) + \pi_1 C_i \mathbb{1}\{b_i > 0\} + D_i \mathbb{1}\{z_i - C_i \leq 0\}.$$

The model predicts that the amount of strategic purchases would be larger with the second-hand




**(a)** Budget sets




**(b)** Strategic purchases as a function of earnings in cash

**Figure 18:** Strategic incremental purchases to the demonetization policy, when reselling in the second-hand market is not allowed

market, as $C_i$ that equates the last inequality in Equation (A.0.8) is larger than $C_i$ that makes the last inequality in Equation (A.0.7) binding. Also, the amount of money saved from reselling ($\theta C_i$) still avoids the tax network, given that most transactions in the second-hand market are not recorded in any taxable accounts.

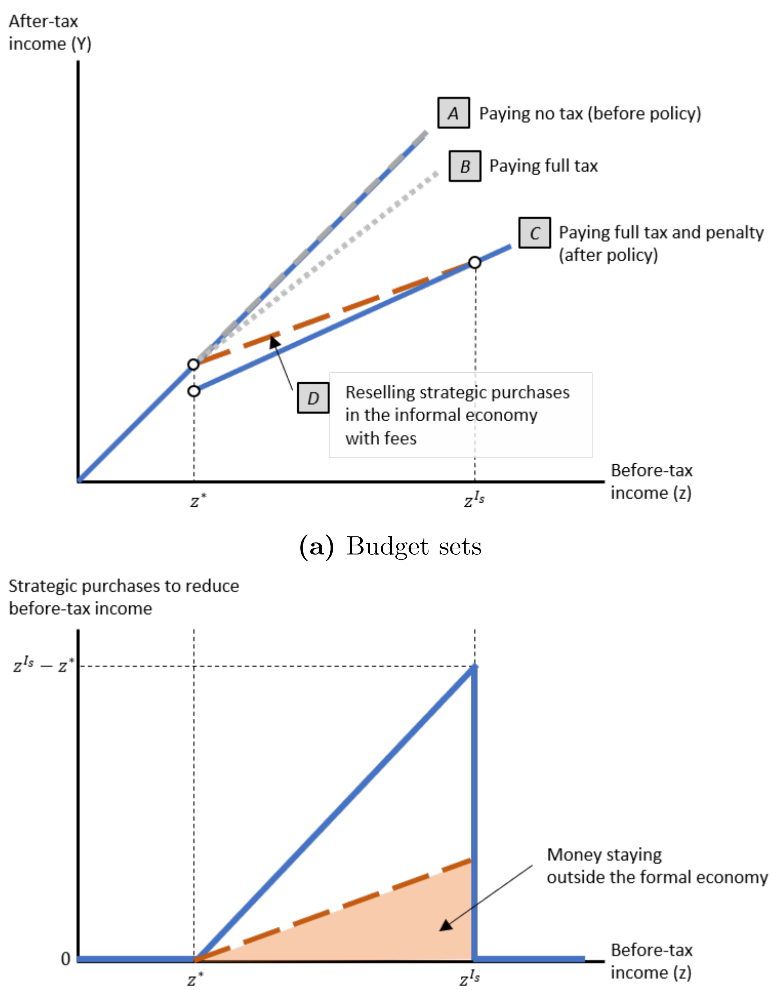
Figure 19 shows how reselling can promote more behavioral responses to the policy. An option of reselling a purchased item at a lower price introduces a new segment of budget set, which is represented as line D in Figure 19(a). It allows households to replace the tax and penalty with the costs associated with reselling the products. If we assume that the reselling cost $\theta C_i$ outweighs the savings in tax and penalty above certain income level ($z^{I_s}$ in Figure 19(a)), then any household that belongs to $[z^*, z^{I_s})$ would be willing to make strategic purchases and resell the items to recoup part of the money (Figure 19(b)). Furthermore, as illustrated above, money used in such transactions remains still off the official tax radar as reselling occurs in the informal economy. Therefore, strategic purchase expansion conflicts with one of the major goals of the demonetization policy.

**3) Accelerated final purchases** Households without any tax evasion still have incentives to make intertemporal substitution and save on the costs of visiting banks to deposit cash. Suppose that household $i$ plans to purchase a good that costs $c_i$ in the near future. If the household has cash in the notes that are to be demonetized, they can accelerate their purchase to be on the day of announcement, pay with the soon-to-be-demonetized notes, and save on the cost of depositing them:

$$\begin{aligned} u_i^{AccPurchase} =& U\left( z_i - c_i - T(z_i - c_i) - \underbrace{D \cdot \mathbb{1}\{z_i - c_i > 0\}}_{\text{Savings in depositing cost}} \right) \\ \geq u_i^{Post} =& U\left( z_i - \underbrace{(1-\delta_i)c_i}_{\substack{\text{Discounted} \\ \text{future planned purchases}}} - T(z_i - c_i) - D \cdot \mathbb{1}\{z_i > 0\} \right) \\ &\text{if} \quad b_i = 0 \quad \text{and} \quad \delta_i c_i \leq D \cdot \mathbb{1}\{z_i - c_i \leq 0\}. \end{aligned} \tag{A.0.9}$$

$\delta_i$ is a discount factor, which is an increasing function of how far in the future the original planned purchase is.[30] This case deviates from the case of purchase expansion (Inequalites (A.0.6), (A.0.7), and (A.0.8)) in two ways. First, the tax penalty is zero because the case applies to a set of households whose tax evasion is zero. Second, the only difference between the utility with and

[30]We do not put the discount factor in the tax function as we assume that the tax is collected on a regular basis at a fixed time schedule for all individuals. In other words, we assume that the tax function incorporates a fixed discount factor that is the same for every household.




**(a)** Budget sets

**(b)** Strategic purchases as a function of earnings in cash

**Figure 19:** Strategic incremental purchases in response to the demonetization policy, when reselling in the second-hand market is allowed

without accelerated purchases is the savings in depositing cost. Other components remain the same because $c_i$ is planned to be purchased regardless of the policy enactment.

The inequalities imply that households are willing to accelerate their purchases as long as the cost of intertemporal substitution ($\delta_i c_i$) is smaller than the savings from the depositing cost ($D_i$). For the condition to be met, households should be able to use up the entire cash holdings via accelerated purchases ($z_i - c_i = 0$), as the depositing cost becomes zero only when there is no cash holdings left to be deposited. Also, the discount factor should be small enough to be outweighed by the benefit from not depositing the banned bills, which limits the degree of purchase acceleration.

**4) Strategic choices of payment method (switching to cash)** Finally, households originally planning to make purchases on the day of announcement can switch to cash from other payment methods to use the cash notes that are about to be demonetized. Here, there is no intertemporal substitution as the purchase is originally planned to take place on the day of announcement, which removes the discount factor $\delta_i$ from the post-utility function ($u_i^{Post}$ in Equation (A.0.9)).

$$\begin{aligned} u_i^{Switching} =& U\left( z_i - c_i - T(z_i - c_i) - \underbrace{D \cdot \mathbb{1}\{z_i - c_i > 0\}}_{\text{Savings in depositing cost}} \right) \\ &\geq u_i^{Post} = U\left(z_i - c_i - T(z_i - c_i) - D \cdot \mathbb{1}\{z_i > 0\}\right) \\ &\text{if} \quad b_i = 0 \quad \text{and} \quad c_i \leq D \cdot \mathbb{1}\{z_i - c_i \leq 0\}. \end{aligned} \tag{A.0.10}$$

Given these types of households responses to the policy, the retailer's profit can be expressed as follows:

$$\Pi_s = \Pi_s^0 + \underbrace{q(\sum_i C_i) - r(\sum_i R_i) - a(\sum_i c_i)}_{=\Delta\Pi_s} \tag{A.0.11}$$

where $\Pi_s$ is the profit of store $s$ under the policy, $\Pi_s^0$ is the counterfactual profit when there is no policy, and $\Delta\Pi_s$ is the change in profit due to the policy. $q(\cdot)$ is a function that maps total incremental final purchases ($\sum_i C_i$) to profit. $r(\cdot)$ is the cost function associated with total incremental returns ($\sum_i R_i$), and $a(\cdot)$ captures any potential costs due to high volume of purchase acceleration (e.g., stockouts, customer management). Throughout our analysis, we assume that $a(\cdot)$ is zero.

## A.2 Evidence against significant measurement errors

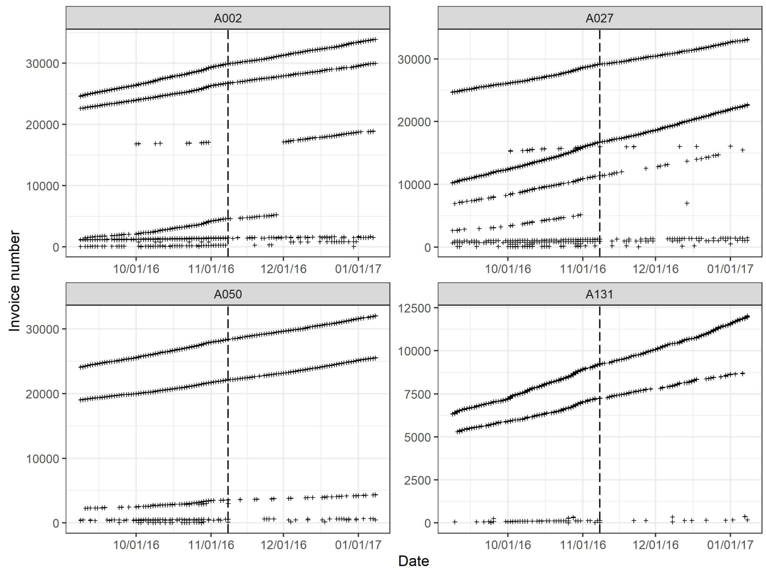
### A.2.1 Minimal impact of back-dated invoices

We provide evidence from the data that back-dated receipts did not take a major portion of the observed transactions on the date of announcement in this particular empirical context. The data provider is one of the largest national retail chains for durable goods in India, and each store has minimal room for flexible changes in customer policies. In particular, unlike the owners of small retail shops, cashiers or managers of the chain's store branches do not have access to manipulate or change the transaction records in the system, which makes the issuance of back-dated receipts extremely challenging. To further confirm this anecdotal evidence, we check the receipt numbers recorded for all the transactions and see if the *sequence* of the invoice numbers changes in a non-ascending way after the policy announcement. Our hypothesis is that, if there were a significant number of back-dated receipts issued by the stores, we should see the receipt numbers out of order around the time of demonetization, as the receipt numbers are automatically generated by the system based on time stamps. Figure 20 shows sequences of system-generated invoice numbers for a sample set of stores. We confirm that all stores do have ascending receipt numbers before and after the policy announcement including the selected sample stores, which are reported to have a significant amount of strategic transactions in our empirical results. As seen in Figure 20, there exist multiple sequences of invoice numbers that start with different alphabets and/or serial numbers for each store, and one might raise concerns that a separate series was created for backdated purchases. To rule out this hypothetical scenario, we analyze all series numbers and we find no such series number which started on the day of announcement. We include this empirical evidence and discussion on it in the Appendix (Section A.2). News article search also reveals that the data provider was not accused of any backdating practices while media extensively covered those incidences whenever they happened at a large scale or at a single national chain. [31]

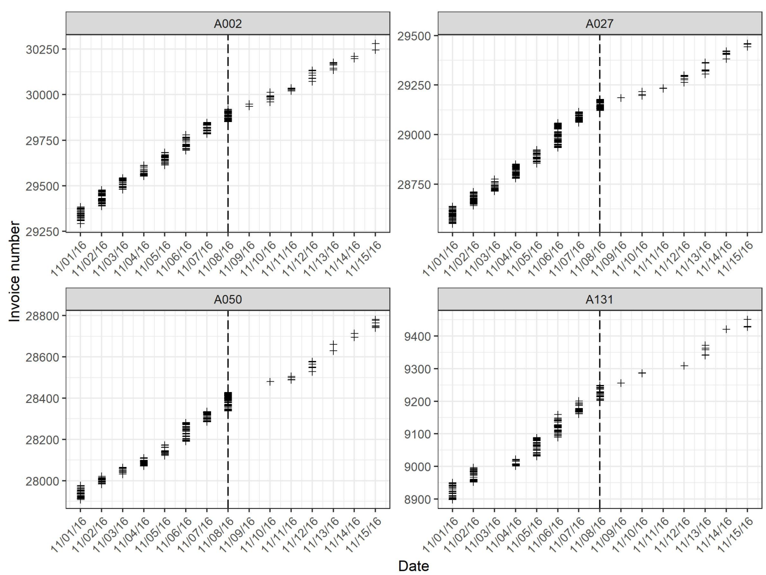
### A.2.2 Substantial increase in cash purchases at grocery stores immediately after the announcement

First, we check whether we find similar spikes in strategic purchases in other categories, namely grocery items. Given the nature of the category, we do not expect to see much strategic returns in this supplementary data set. However, we hypothesize that, if a significant amount of strategic purchases indeed happened before midnight after the announcement, a drastic increase in cash purchases would be observed after the announcement in grocery stores as well. The supplementary data set is from one of the five largest supermarket chains in India, which records transactions in

[31] "Lens on jewellers who sold gold bars and showed back-dated entry," The Times of India, December 16, 2016 "ED files charge sheet in demonetisation case against Hyderabad dealer," Business Standard, June 1, 2021 "Demonetisation: Old money can still buy you hairdos and spa sessions," The Economic Times, November 16, 2016.




**(a)** All invoice sequences




**(b)** Zoom-in to a one particular sequence

**Figure 20:** Sequences of system-generated invoice numbers for cash purchases, by sample stores

six stores spread over four major cities of India — Bangalore, Delhi, Hyderabad and Indore - from August 2016 to December 2016. Unlike the main data set, it has a more detailed time stamp on every transaction, which allows us to see purchase patterns on an hourly basis.

Figure 21 shows hourly cash purchases of grocery items in different stores on the day of announcement. Red lines denote hourly cash purchases on the day of announcement in those cities with high estimated strategic transactions in our main analysis (see Figure 22 for comparison with the results from the main data set). Black solid lines represent the same for those cities with low estimated strategic transactions. Dashed vertical line marks 8:00 PM when the announcement was made. As the announcement took place on Tuesday, we also plot hourly transaction data in other Tuesdays from August to December as benchmarks (plotted in gray). Confirming our hypothesis, cash purchases in grocery stores do increase after the announcement in those cities with high estimated strategic transactions according to the main data set.[32] This further supports our findings that many consumers reacted immediately after the announcement to use their soon-to-be-demonetized cash notes.

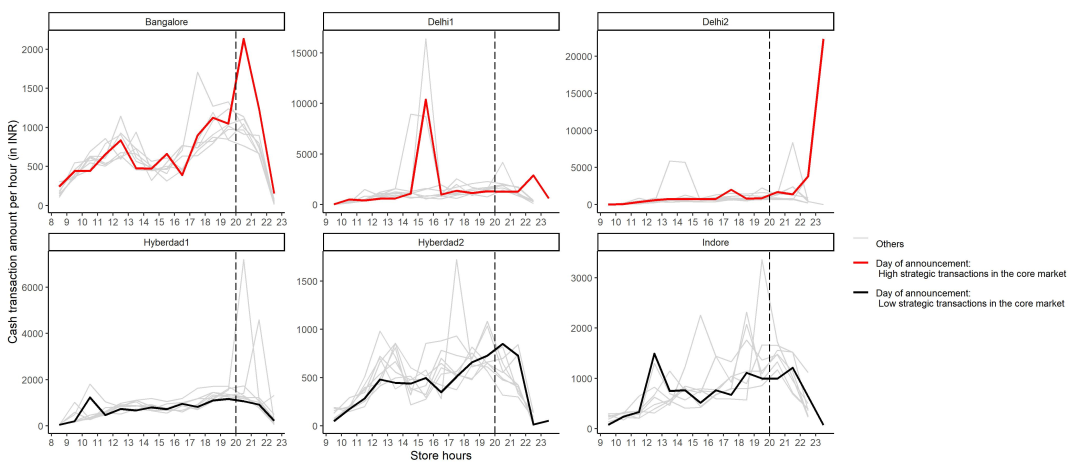


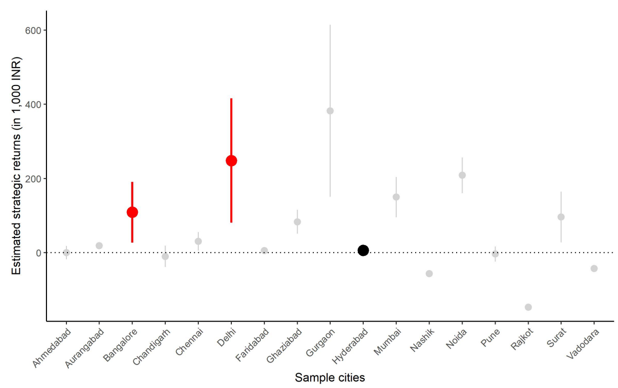

**Figure 21:** Supplementary data analysis: Cash purchases in grocery stores

### A.2.3 Institutional details

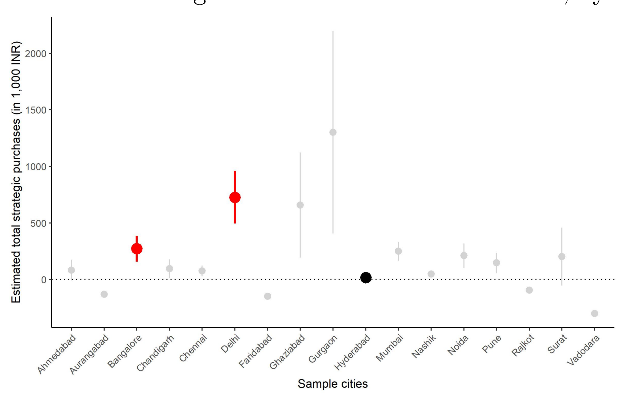
Several institutional details make rush transactions within 4-hour window more plausible. Most large cities in India are small enough so that anyone can reach from one end to the other end within an hour.[33] Also, like in stores in the U.S., stores cannot force customers to leave at the closing hour if customers succeed in stepping into the store before it closes. Figure 21 gives suggestive evidence

[32] An observed spike between 3 PM and 4 PM in Delhi 1 store is because of local farmers market happening regularly, which is implied by multiple gray lines that have similar peaks.

[33] Travel Time Report Q1 2019 vs Q1 2018, MoveInSync.




**(a)** Estimated strategic returns in the main data set, by cities




**(b)** Estimated strategic purchases in the main data set, by cities

**Figure 22:** Main data analysis: Estimated strategic transactions by cities

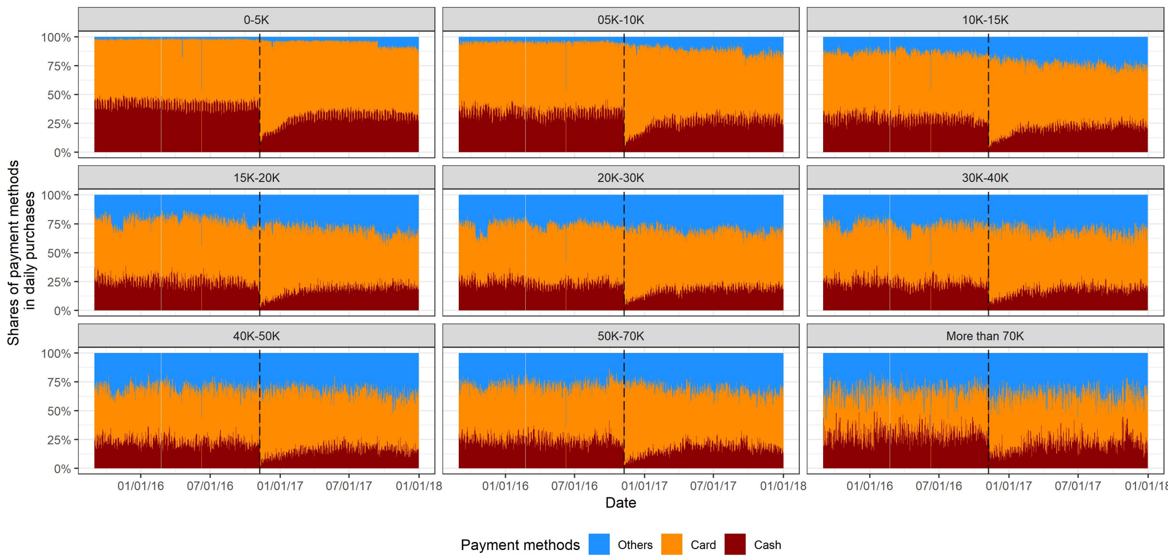



**Figure 23:** Changes in payment method choices over time

of this behavior; 4 stores out of 6 - Delhi 1, Delhi 2, Hyderabad 2, and Indore - record positive amount of transactions even after their usual closing hours (10:00 pm).

### A.3 Long-term effects of demonetization on payment choices

We observe some persistent changes in the choices of payment methods after the demonetization policy, as intended by the government. Overall, households' cash payment activities gradually increase after a drastic drop right after demonetization, but they stay lower than the pre-demonetization level. Figure 23 shows model-free evidence of this long-term effect.

To estimate store-specific long-term effects of demonetization, we use the following regression and estimate $\delta$:

$$\begin{aligned}
&\text{For } t \in \{t | 1 \le t \le T \text{ and } t \notin [t_0, t_0 + 60]\} \text{ and } k = \text{Cash}, \\
&y_{skt} = \sum_{p=1}^{p_1} a_{sp}\text{Diwali}_t^p + \sum_{p=1}^{p_2} b_{sp}\text{Dussehra}_t^p + \sum_{p=0}^{p_3} c_{sp}t^p \\
&\qquad + \sum_m \mathbf{1}\{\text{Month} = m\} d_{sk} + \sum_w \mathbf{1}\{\text{Day of week} = w\} e_{sk} \\
&\qquad + \delta_s \text{Demonetization}_t + \iota_{skt} \qquad \text{(A.0.12)}
\end{aligned}$$

where $s$ denotes store and $t_0$ is the day of policy announcement and $\text{Demonetization}_t$ is 1 after the policy became effective and 0 otherwise. For this estimation, we remove observations in the

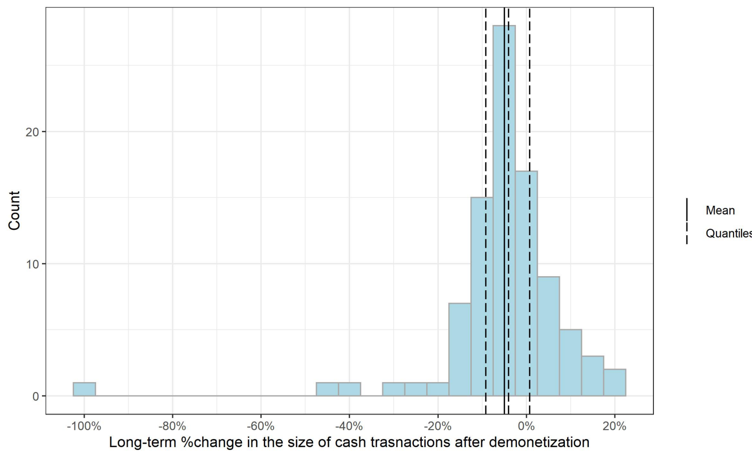



**Figure 24:** Estimated store-specific % changes in the size of cash transactions after demonetization

period of two months after demonetization to only include stabilized patterns. Figure 24 reports the distribution of estimated $\delta$ across 92 stores. As suggested in Figure 23, 70% of the stores (64 out of 92) negative point estimate of $\delta$.

Table 9 shows store-level heterogeneity in long-term changes in cash transactions after demonetization. Column (1) uses the full sample of 92 stores, while Column (2) uses a sub-sample of 81 stores with average rent prices. In both columns, a store is likely to experience a larger drop in cash transactions after demonetization if the store's daily sales were cash-intensive before demonetization (the first row) and average rent price is higher (the last row).

**Table 9:** Heterogeneity in long-term effects of demonetization policy

| | *Dependent variable:* | |
|---|---|---|
| | Long-term % change in the size of cash transactions after demonetization | |
| | (1) | (2) |
| % Cash transactions in daily sales before demonetization | $-0.568^{***}$ | $-0.734^{***}$ |
| | (0.211) | (0.267) |
| Strategic returns (as % of daily sales) | $-0.073$ | $-0.067$ |
| | (0.065) | (0.066) |
| Accelerated purchases (as % of daily sales) | $-0.005$ | $-0.005$ |
| | (0.016) | (0.019) |
| Payment switching (as % of daily sales) | $-0.030$ | $-0.046$ |
| | (0.056) | (0.059) |
| Incremental purchases (as % of daily sales) | 0.021 | 0.022 |
| | (0.022) | (0.025) |
| log(Av. Rent) | | $-0.050^{**}$ |
| | | (0.025) |
| Constant | $0.128^{**}$ | $0.633^{***}$ |
| | (0.060) | (0.209) |
| Observations | 92 | 81 |
| $R^2$ | 0.120 | 0.255 |
| F | $2.346^{**}$ | $4.224^{***}$ |
| *Note:* | | $^{*}$p<0.1; $^{**}$p<0.05; $^{***}$p<0.01 |