Digital Payments and Consumption: Evidence from the 2016 Demonetization in India *

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Abstract

We study how consumer spending responds to digital payments, using the differential switch to digital payments across consumers induced by the sudden 2016 Indian Demonetization for identification. Usage of digital payments rose by 3.38 percentage points and monthly spending increased by 3% for an additional 10 percentage points in prior cash dependence. Spending remained elevated even when cash availability recovered. Robustness analyses show that the spending response is not driven by income shocks, credit supply, price changes, or consumers' moving to the formal market. We provide evidence that digital payments increase consumer spending due to subdued salience.

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1 Introduction

The increasing digitization of the global economy is changing how products and services are produced, distributed, and sold all around the world. Digital payment instruments such as debit cards, credit cards, and mobile money have gained widespread popularity. Globally, the share of adults using digital payments rose by 11 percentage points from 41% to 52% between 2014 to 2017 (Demirguc-Kunt et al., 2018, Chapter 4). Motivated by the reduction of paper currency operational costs and the improvement of financial inclusion brought by digital payment technologies, several governments have launched official programs to promote digital payments.[1]

In this paper, we study whether and how households' adoption of digital payments affects their spending decisions. Theoretically, digital payments can affect consumption through two channels. Digital payments reduce transaction costs as they render storing, transporting, and counting paper bills and coins unnecessary. They are also less salient than cash. Both mechanisms lead to a prediction that adoption of digital payments increases spending. Given the rapid pace at which digital payments are displacing cash, understanding and assessing this effect is important.

Testing these theoretical predictions, however, is challenging empirically. The observed use of digital payments is an equilibrium outcome that is affected by the availability of digital payments as well as both consumers and merchants' awareness of and willingness to use digital payments. On the one hand, consumers do not have equal access to digital payments. On the other hand, merchants are not uniformly willing to accept digital payments. Small or standard-alone merchants quite often put restrictions for digital payments such as minimum spending.[2] Even in a setting where merchants are willing to accept digital payments and consumers have access, consumers can often choose to pay a small receipt with cash and switch to digital payments for a larger receipt. This leads to a mechanical relationship between receipt size and cash usage, hindering useful inference of the impact of digital

[1]The Prime Minister Jan Dhan Yojana scheme and RuPay cards in India, the Singapore Quick Response (SG QR) code in Singapore, and the Faster Payment System (FPS) in Hong Kong are some examples of government official programs. Relatedly, governments in Mexico, Brazil, the South Africa, and Mongolia among others digitize government transfer payments.

[2]Consumers' adoption of digital payments can feed back into merchants' adoption choice, and vice versa (e.g., Higgins, 2020).

payments on spending.[3]

To overcome this empirical challenge, we focus on a unique episode in the adoption of digital payments. On November 8th, 2016, the Indian government unexpectedly removed 86% of the existing currency in circulation from legal tender, effective at midnight. New notes were not immediately available; rather, they were gradually introduced over the next several months. This policy, referred to as "Demonetization," resulted in a sudden and sharp decline in the availability of cash that could be used for spending transactions and a forced uptake of digital payments. In the sample of supermarket purchases we study, the average cash usage dropped 20 percentage points in November 2016, from 72% in the previous month. The majority of this gap is filled by an increase in debit card usage.

To tease out the effect of digital payments adoption, we exploit variation in individual-level cash dependence. Since the Demonetization made a large number of existing bills cease to be a viable medium of exchange but made no restriction for using digital payments, consumers who relied more on cash prior to this policy were more affected by the forced switch to digital payments. We construct an individual-level measure of forced adoption as the level of cash usage prior to the Demonetization announcement, using the detailed records of payment methods.

We compare changes in spending patterns across individuals with varying degrees of prior cash dependence in a difference-in-differences framework. In the panel regressions, we include a host of fixed effects to control for various confounding factors. Individual fixed effects absorb fixed individual characteristics. In addition, district$\times$time fixed effects control for the impacts of underlying economic conditions that can vary by district, such as the district-specific currency supply shocks (Chodorow-Reich et al., 2019).

We validate that prior cash dependence captures the forced switch to digital payments. Usage of digital payments rose by 3.38 percentage points for an additional 10 percentage points in prior cash dependence following the Demonetization. Such a forced switch to digital payments is associated with a marked and highly statistically significant increase in spending: moving from the 25th to the 75th percentile of prior cash dependence is associated with a 15% increase in spending. In addition,

[3] Some prior studies use experimental settings to document the increase in consumers' willingness-to-pay associated with cards (e.g., Feinberg, 1986; Prelec and Simester, 2001). While the experimental settings can alleviate some of the confounds to a causal mechanism, they typically do not involve real money transactions that are comparable to actual spending of typical households. This leads to limited generalizability and quantitative relevance of these experimental findings.

we find that the increase in spending remained persistent till September 2017, the end of our sample period, despite the demonetized notes being replenished a few months after November 2016.

We conduct several additional analyses to sharpen our understanding of the spending response. First, we analyze different types of spending. We find that previously cash-reliant individuals increased their non-food spending and durable spending relative to their food spending and non-durable spending. Second, we examine measures of supermarket spending variety and shopping intensity. We find that these measures respond to the forced switch to digital payments in a consistently positive and highly significant manner. Third, we also investigate the composition of the observed increase in spending by examining the quantity and price of goods purchased. We find strong evidence that consumers who were forced to switch to digital payments purchased expensive goods in narrowly-defined categories following the Demonetization. Finally, we examine response heterogeneity across individuals. We uncover substantial heterogeneity whereby lower-spending individuals experienced a much larger switch to digital payments and a much larger spending response relative to higher-spending individuals.

We address four potential threats to our identification of the effect of digital payments on consumer spending. First, we test whether a spurious correlation between prior cash dependence and income shocks might explain our findings. We split our sample by whether an individual paid large receipts with cash in the pre-Demonetization period, a proxy for drawing income from the informal sector, We find that consumers who engaged in informal economic activities are characterized by a higher prior cash dependence and a lower spending response. The income differential, if exists, likely contributes to a downward bias of the estimated coefficient.

Second, we consider the possibility that our results might be driven by an increase in credit supply targeted to by previously cash-reliant individuals. A higher prior cash dependence is associated with a slightly lower credit card usage following the Demonetization, which is consistent with the literature on credit history and access to credit. When we examine existing users, new users, and non-users of credit cards separately, we find suggestive evidence for an increase in credit supply to existing and new users. Nonetheless, these two groups together account for a small fraction of consumers. The results derived from non-users who represent the majority of our sample are virtually unchanged from our main results derived from the full sample.

Third, one might worry that the effect of digital payments on spending is mechanically driven by increases in product prices. To test this channel, we measure the exposure to the Demonetization-induced adoption of digital payments for each product using the spending profile of its consumers and compare products of different levels of exposure. We find no evidence that high-exposure products experienced a larger price increase than low-exposure products.

Fourth, if the Demonetization leads to a shift from unobserved purchases in the informal markets to observed purchases in the formal market, our estimate can be upward biased. The exclusion of new consumers that arrived after the Demonetization from our analysis implies that we are not picking up the most obvious form of this shifting. The markedly higher increase in non-food spending and in durable spending runs contrary to what a shift of purchases from informal markets to the supermarket among existing consumers would predict, as non-food and durable products are not commonly available in informal markets. We also test for heterogeneous shifts of purchases across consumers. One would expect consumers who previously bought non-food goods from the supermarket to have a higher spending response as they shift their food purchases from informal markets to the supermarket. We stratify our sample to separately examine consumers of different levels of prior food spending and find the opposite: high prior food spending is associated with a higher spending response.

According to our estimates, a forced switch to digital payments induced by the Demonetization leads to a sharp increase in consumption by previously cash-dependent households. It remains to be seen whether the effect is driven by lower transaction costs or subdued salience. To analyze which of these two channels qualifies as a more plausible explanation for our empirical finding, we exploit the differential impact of salience of cash on offline and online purchases and compare consumer spending behaviors in the supermarket with an online grocery store. Online purchases of physical goods are characterized by a time lag between the purchase decision and the delivery of goods. At the time of the purchase decision, both cash payment (i.e., cash on delivery) and digital payments involve no physical exchange of money between hands. Therefore, paying for an online purchase with cash invokes the behavioral costs associated with cash payment being effortful, instant, and memorable to an lesser extent than paying for an offline purchase with cash.

Crucially, the transaction costs associated with cash apply equally to online and offline shopping. As in our main analysis using the supermarket data, we exploit the cross-sectional variation in cash dependence prior to the Demonetization at the individual consumer level to estimate the forced switch to digital payments and associated spending response using data from a large online grocery retailer. We find that the forced switch to digital payments by previously cash-reliant individuals is stronger in the online retailer panel. On the contrary, the spending response is much muted. The estimated increase in spending in the online retailer panel is one-fifth of the effect found in the supermarket panel. The difference in estimated spending responses between the two panels suggests that the large spending response we observe in the supermarket panel is likely to reflect the behavioral forces as opposed to the transaction costs.

This paper engages with several strands of literature. First, we contribute to the literature on the economic impacts of digital payments. The interest charges on credit cards pose substantial costs.[4] Debit cards, which share similar acceptance, security, portability, and time costs as credit cards and have become a close substitute for credit cards over time (Zinman, 2009), are not cost-free for households. Stango and Zinman (2009) analyze the costs consumers pay for debit and credit cards and conclude that a large fraction of the total costs can be avoided by minimal behavior changes. Moreover, digital payments can affect household savings (Suri and Jack, 2016; Bachas et al., 2020), risk sharing (Jack and Suri, 2014), and the feedback between merchants' adoption and consumers' adoption (Higgins, 2020). Thus far, this literature has largely taken the consumption bundle as given. Our paper, by contrast, emphasizes that digital payments can directly affect the consumption bundle through their subdued salience. Our paper is also related to the findings by Agarwal et al. (2018), Chodorow-Reich et al. (2019), and Crouzet et al. (2020) that the drying-up of cash due to Demonetization leads to a substantial and persistent rise in the adoption of digital payments.

There is a growing literature that studies the impacts on consumer spending of

[4] Simultaneously lending "low" in bank transaction accounts and borrowing "high" on credit cards is prevalent among households, particularly in the US; this phenomenon is widely viewed as an apparent violation of the no-arbitrage condition and therefore termed the "credit card debt puzzle." The interest rate differential that exceeds 10% per year is a substantial cost for the borrowing high and lending low households. In accounting for this seeming puzzle, researchers have proposed rational explanations such as the implicit value of liquid assets arisen from payment and credit market frictions (Zinman, 2007; Telyukova, 2013) and psychological factors such as present-biased preferences (Meier and Sprenger, 2010) and self control (Bertaut et al., 2009).

government policies that do not affect household income directly. D'Acunto et al. (2018) study an unexpected announcement of a future increase in value-added tax in Germany and document its sizable effects on households' inflation expectations and willingness to purchase in Germany. Relatedly, Baker et al. (2019) find a substantial tax elasticity for car sales in anticipation of future sales tax changes in the United States. Our paper differs in several ways. First, we show that our channel operates through salience of payment instruments, whereas the unconventional fiscal policy operates through intertemporal substitution. Moreover, we use actual transaction data of a broad set of consumption goods to characterize households' spending response. Finally, we document a consumption response in the absence of price changes, as opposed to a scenario where consumption tax changes affect the prices directly.

Our paper also contributes to the policy debate about the costs and benefits of moving to a cashless economy. Cash poses substantial operational costs to the economy as a whole: the central bank is responsible for manufacturing, quality control, circulation control, and counterfeit detection; banks spend resources in managing their ATMs, branches, teller services as well as deposit collection and handling of coins.[5] Moreover, there are indirect, societal costs of cash such as curbing the effectiveness of monetary policy by putting a floor on the nominal interest rate and facilitating illegal activity and tax evasion (Rogoff, 2017). Moving to digital payments can potentially reduce these direct and indirect costs and therefore promote economic growth and efficiency. Given the heavy use of cash in India and many other emerging economies, such gain could be substantial. Our paper provides causal evidence that digital payments lead to increased spending and documents that the spending response is primarily driven by the salience channel. This finding suggests that a move from cash towards digital payments could unintentionally encourage people to over-spend, which could undermine sound personal financial planning.

The paper proceeds as follows: Section 2 provides an overview of the November 2016 Demonetization in India. Sections 3 and 4 describe the data and the empirical approach. Section 5 presents our main results, followed by analysis to address alternative explanations in Section 6 and to disentangle the underlying channel in Section 7. Section 8 concludes.

[5] In the primarily cash-based Indian economy, the total currency operation costs is estimated to be 210 billion rupees (3.15 billion dollars) annually (Mazzotta et al., 2014).

2 The 2016 Demonetization in India

On November 8th, 2016, at 8:15pm local time, the Indian Prime Minister Narendra Modi announced a Demonetization scheme in an unscheduled live television address: The two largest denomination notes, the 500 and 1000 rupee notes (7.5 and 15 dollars, respectively), would cease to be legal tender and be replaced by new 500 and 2000 rupee notes. Effective at midnight, holders of the old notes could deposit them at banks but could not use them in transactions. The stated objectives of the policy were to weed out black money, remove fake paper notes, and reduce corruption, tax evasion, and terrorism.[6]

At the time of the announcement, the demonetized 500 and 1000 notes accounted for 86% of currency in circulation. There was prolonged unavailability of new notes due to printing press constraints. Before the November 8th announcement, the government did not print and distribute a large number of new notes to maintain the secrecy of the policy. Total currency declined overnight by 75% and recovered only slowly over the next several months (Chodorow-Reich et al., 2019).

Such a large drop has profound impacts as India was a primarily cash-based economy. Currency in circulation accounts for almost 18% of India's GDP, compared to 3.5% to 8% in the United States and the United Kingdom. About 87% of the value of all transactions in 2012 was in cash (Mazzotta et al., 2014). The Reserve Bank of India, India's central bank, proposed a vision "to proactively encourage electronic payment systems for ushering in a less-cash society" in 2012.[7] The subsequent policies had not changed the dominant role of cash payment as of 2015. Although the number of debit cards issued increased 64% from 2013 to 2015, usage of debit cards at purchase transactions (point-of-sales machines) accounted for only around 12% of total volume and 6% of total value of debit card transactions as of October 2015.[8] The large and sudden Demonetization event in November 2016 represents a forced switch away from using cash for transactions.

[6] The Indian government had demonetized paper notes on two prior occasions — once in 1946 and once in 1978 — in both cases, the goal was to combat tax evasion and black money.

[7] Source: RBI's Payment System Vision Document (2012-15), available at https://rbidocs.rbi.org.in/rdocs/PublicationReport/Pdfs/VDBP270612.pdf.

[8] The remaining transactions are ATM transactions such as cash withdrawals and deposits, which would map into using cash at purchase transactions. Source: ibid.

3 Data and Summary Statistics

We use anonymized transaction-level data from a large Indian supermarket chain. The data comprise all purchases in 171 stores in twenty-one districts of five states from April 2016 to September 2017. For each purchase transaction, we observe the date and address of the store where the purchase was made. We also observe the payment method(s) and their shares if multiple payment methods were used to pay for the purchase occasion. The main payment method categories include cash, debit cards, credit cards, and mobile payments.

Figure 1, which plots the overall shares of different payment methods in the universe of all supermarket transactions over time, demonstrates the rapid switch to digital payments following the Demonetization. The share of cash in payment methods dropped 20 percentage points in November 2016, from 72% in the previous month. The majority of this gap is filled by an increase in debit card usage. Usage of other payment methods (e.g., credit cards and mobile payments) remains low. The shift from cash payment to cashless payments is consistent with Agarwal et al. (2018), Chodorow-Reich et al. (2019), and Crouzet et al. (2020), among others.

We conduct our analysis at the individual consumer level and aggregate all purchases to monthly observations for each individual in our panel. Measures we use in our analysis include payment instruments usage, total spending and its composition, and spending variety and shopping intensity. Additional details for sample construction and variable definitions can be found in Online Appendix A.

Table 1 presents the summary statistics of these variables. Except for payment instruments' respective shares in panel (a), we first calculate the within-individual average of each variable in the seven months prior to the Demonetization (2016:04–2016:10) and then report the summary statistics in the cross-section of individuals. For the variables in panel (a), we report the cross-sectional summary statistics of within-individual averages for the 2016:04–2016:10 and 2016:11–2017:09 periods separately.

The average cash usage drops from 72% to 60% following the Demonetization; such a decline is mostly compensated by an increase in debit card usage from 22% to 32%. Usage of mobile payments and credit cards also increases modestly from the respective pre-Demonetization level. The average monthly spending prior to Demonetization is 830.7 rupees (13 dollars). As a comparison, monthly gross disposable income per capita is 6973 rupees (104.5 dollars) in 2016 according to the

Central Statistics Office. The average monthly spending we observed in our data accounts for 12% of the monthly gross income. Food and non-food spending accounts for 78% and 22% of total spending, respectively. The average probability of having positive food spending in a given month is 94% while the average probability of having positive non-food spending in a given month is 54%. When we split the purchases alternatively by durability, we find that non-durable spending accounts for the majority (over 99%) of the consumer spending we observe, consistent with that the majority of products sold in the supermarket chain are non-durable products. Moreover, the average probability of having positive durable spending in a given month is less than 5% while the average probability of having positive non-durable spending in a given month is 100%.

4 Empirical Approach

We are interested in estimating the elasticity of spending with respect to the usage of digital payments. Theoretically, digital payments can affect consumption in two ways. Digital payments reduce transaction costs as they render storing, transporting, and counting paper bills and coins unnecessary. They are also less salient than cash. Both mechanisms lead to a prediction that digital payments increase spending through their lower transaction costs and lower salience.

However, important confounding factors prevent a straightforward causal identification through an ordinary least squares (OLS) regression of spending on a measure of digital payment usage. One omitted variable is the access to digital payments, which is certainly neither equal nor random in the population. Prior research (e.g., Borzekowski and Kiser, 2008) shows that access to digital payments can be influenced by socioeconomic factors — income, wealth, education, etc. Observing a positive correlation between the level of spending and using digital payments is consistent with the income effect by which higher-income individuals have better access to digital payments and spend more relative to lower-income individuals. Moreover, causality can run in the opposite direction even if we equalize the access to digital payments across individuals: which payment method is used and therefore observed by the econometrician in the actual transaction data is an endogenous choice typically affected by the transaction amount. Smaller receipts tend to be paid by cash due to convenience.[9] Both the omitted variable and the reverse causality are

[9]In our sample, the mean (median) receipt amount paid with cash is 204.28 (88) rupees while the

likely to bias the OLS estimate of the causal parameter of interest – the coefficient of the digital payment usage on an individual's spending – upward.

To resolve this identification challenge, ideally one would randomly assign identical consumers to cash and digital payment methods that are both accepted in the merchant. In this randomized setting, the difference in spending amount between cash users and digital payment users would be orthogonal to all individual characteristics and therefore reflect the impact of payment methods. We adopt a quasi-random approach, exploiting the variation in individual consumers' exposure to the sudden dry-up of cash due to the Demonetization. The Demonetization drained the currency in circulation and affected individuals' ability to use cash in transactions, therefore forcing cash-dependent individuals to switch to digital payments. An individual's exposure to this forced switch is proportional to his/her prior cash dependence. We compare changes in spending patterns across individuals with varying degrees of prior cash dependence in a difference-in-differences (DiD) framework.

We conduct the analysis at the consumer-month level. Our baseline panel regression specification is as follows:

$$y_{i,t} = \mu_i + \pi_{d,t} + \beta \cdot (PriorCashDependence_i \times Post_t) + \varepsilon_{i,t} \quad (1)$$

$y_{i,t}$ is a measure of spending behavior (spending amount, payment pattern) of consumer i in month t. The key variable of interest is the interaction term between $PriorCashDependence_i$, an individual-level measure of prior cash dependence defined as the average share of spending paid by cash from April 2016 to October 2016, and $Post_t$, an indicator for post-Demonetization months. Its coefficient β measures the forced switch to digital payments.

The identifying assumption central to a causal interpretation of our DiD estimates is that individuals with varying prior cash dependence share parallel trends. We test whether pre-treatment trends are parallel in the next section. The question, as in any DiD set-up, is whether post-treatment trends would have continued to be parallel if not for the Demonetization. To mitigate the concern that they would not have been, we include a host of fixed effects to control for confounding factors that are invariant in certain dimensions. Individual fixed effects, μ_i, absorb fixed individual characteristics, whether observed or unobserved, disentangling the De-

mean (median) receipt amount paid with digital payments is 620.79 (292.5) rupees.

monetization shock from socioeconomic and demographic sources of omitted variable bias. Time fixed effects, $\pi_{d,t}$, further neutralize the impacts of common trends. The substantial variation in the supply of new paper bills after the Demonetization announcement across districts (Chodorow-Reich et al., 2019) likely causes the common trends of observed within-individual changes in payment choice and spending to differ across different districts. To fully control for the impact of district-specific currency supply shocks, we include a separate set of time fixed effects for each district (hence the subscript d).[10]

This specification augments a standard DiD specification by taking a flexible and agnostic approach to account for treatment intensity (subsumed by individual fixed effects) and the post-treatment indicator (subsumed by district×time fixed effects). Standard errors in all regression analyses are doubly clustered at individual level and at month level.

In addition, we study the dynamics of the spending response using the following distributed lag model:

$$y_{i,t} = \mu_i + \pi_{d,t} + \sum_{t=-6}^{10} \beta_t \left(PriorCashDependence_i \times \mathbb{1}_t \right) + \varepsilon_{i,t} \tag{2}$$

where $\mathbb{1}_t$ is an indicator variable for each of the months before and after the Demonetization. April 2016, the first month in our sample period, is the omitted baseline group. In this dynamic specification, the coefficient β_0 measures the immediate response in spending during the Demonetization month. $\beta_1, \cdots, \beta_{10}$ track the spending response one month, two months, $\cdots$, and ten months after the Demonetization, respectively. Similarly, $\beta_{-6}, \cdots, \beta_{-1}$ capture the difference of trends in spending across individuals with varying prior reliance on cash in each of the six pre-Demonetization months.

Last but not least, we examine category-level outcome variables by running the following regression for consumer i's spending in category c in month t:

$$y_{i,c,t} = \mu_{i,c} + \pi_{c,d,t} + \beta \cdot \left(PriorCashDependence_i \times Post_t \right) + \varepsilon_{i,c,t} \tag{3}$$

In this specification, the coefficient β measures the impact of Demonetization.

[10] We find that district-level currency shocks are indeed correlated with spending in Online Appendix Section B. This correlation makes it important to include district×time fixed effects, as opposed to just time fixed effects, for a cleaner identification.

The individual×category fixed effects $\mu_{i,c}$ control for the potential differences in spending profiles across consumers; the category×district×time fixed effects $\pi_{c,d,t}$ subsume factors such as the seasonality in product demand and supply and the supplier's pricing responses that are allowed to differ across districts.

5 Evidence for Spending Increase Induced by Digital Payments

We begin by showing the differential response of digital payment usage and spending to the Demonetization across indidivuals with different levels of prior cash dependence. To sharpen the results, we later analyze the dynamics and study response heterogeneity across different types of spending and across different types of individuals.

5.A Analysis of unconditional patterns

We compare "full cash users" whose prior cash dependence is 100% with other consumers whose prior cash dependence is lower than 100% ("mixed cash users") in Figure 2. Panel (a) plots the average share of spending paid by cash for the two groups over time. In the seven months before the Demonetization, full cash users had a 100% cash usage by construction and mixed cash users had a stable average cash usage of 42%. The average cash usage during this period likely reflects the equilibrium choice for payment method in the steady-state absent from a cash shortage such as the Demonetization. The difference in prior cash dependence corresponds to the exposure to the Demonetization: In November 2016 when the Demonetization occurred, full cash users reduced their cash usage by more than 20 percentage points whereas mixed cash users reduced by 11 percentage points. This implies that the Demonetization disproportionately affected the payment choice of cash-dependent consumers and forced them to switch to digital payments. Cash usage by both groups continued to decrease in December 2016 before rebounding in 2017. In the new equilibrium which was reached in March 2017, full cash users prior to the Demonetization exhibit a 80% cash usage and mixed cash users appear to return to their previous cash usage of 42%.

Panel (b) plots the average level of the natural logarithm of spending amount for the two groups over time. Overall, full cash users have a lower spending than mixed cash users, consistent with the notion that wealthlier and higher-income individuals have better access to digital payments than less wealthy and lower-income individuals. The average spending of both groups appears to be stable in the seven months prior to the Demonetization. Not only does this dynamic pattern in the pre-period reassure the exogeneity of the Demonetization, but it also lends credence to our research design's core identification assumption of parallel trends. In November 2016, full cash users increased their spending by more than 30%, whereas mixed cash users had little change in their spending. In the ten months following the Demonetization, the average spending of full cash users does not appear to reverse back to pre-Demonetization levels despite replenishment of the demonetized notes.

This graphical analysis of unconditional patterns demonstrates our main finding: consumers who used to rely on cash for supermarket spending were forced to switch to digital payments by the Demonetization and increased spending significantly. Such a spending response persists despite the gradual replenishment of the demonetized notes. In the multi-group comparison of cash usage and spending over time (Online Appendix Figure OA.2), we show that the effect is monotone in the pre-determined exposure and not driven by a few outlier consumers or consumer groups.

5.B Regression analyses of average response

Next, we present statistical results in the DiD panel regression setting. Table 2 reports the estimates from equation (1).

Column 1 shows the forced switch to digital payments induced by the Demonetization: an increase of 10 percentage points in the prior cash dependence is associated with a 3.38 percentage point drop in cash usage, or a 3.38 percentage point increase in digital payments usage, following the Demonetization. Columns 2–4 decompose digital payments into debit cards, mobile payments, and debit cards. The decline in cash usage is mostly compensated by an increase in debit card usage. Adoption of mobile payments also has a statistically significant increase, albeit with a minuscule economic magnitude. On the contrary, high prior cash dependence leads to a small yet significant lower credit card usage following the Demonetization.

Column 5 reports the result for the level of spending amount. The estimate indicates that an increase of 10 percentage points in the prior cash dependence is associated with an increase of 23.93 rupees in monthly spending. An analysis using the inter-quartile range of prior cash dependence can demonstrate the economic significance of this estimate: the 25^{th} and 75^{th} percentiles of prior cash dependence are 50% and 100%. Therefore a consumer at the 75^{th} percentile increases spending by 119.65 rupees relative to a consumer at the 25^{th} percentile. This additional spending corresponds to approximately 14% of the unconditional mean of monthly spending in the pre-Demonetization period. Column 6 reports the result for the natural logarithm of spending amount. According to the estimate from this specification, an increase of 10 percentage points in the prior cash dependence is associated with a 3.07% increase in monthly spending. Therefore, a consumer at the 75^{th} percentile of prior cash dependence increases spending by 15.35% relative to a consumer at the 25^{th} percentile.

Columns 1–3 of Table 3 show the estimates obtained from the sample excluding full cash users prior to the Demonetization. In this subsample, the effects on the usage of each payment method and on the absolute level of spending are quantitatively similar, whereas the effect on log spending is smaller. Columns 4–6 show the results estimated from the sample excluding the first three months following the Demonetization announcement (November 2016, December 2016, and January 2017). These estimates confirm that the spending response is unchanged when cash made a comeback to the economy.

5.C Dynamic pattern

We also examine the dynamic pattern of the spending response in the regression setting. The Demonetization resulted in a sudden dry-up of cash that persisted for several months. It is possible that the eventual replenishment of cash would undo some of the forced switch to digital payments and therefore restrict the effect on spending. However, the impact of cash availability on payment choice can be highly asymmetric: while a sudden dry-up of cash forces consumers to seek digital alternatives, the replenishment of cash may become irrelevant for them. Consider the following scenario: a consumer who was not familiar with digital alternatives to cash adopts some digital payments and enjoys the associated benefits such as the ease of record-keeping and no longer needing to carry and count bills and coins. She is unlikely to go back to the traditional way of paying by cash. The sustained lower cash usage and higher spending by the consumers who previously used cash payment exclusively in the post-Demonetization period in Figure 2 provide support for this possibility.

To examine this, we estimate equation (2) for two outcome variables, cash usage and log spending, and plot the estimated coefficients in Figure 3.

Panel (a) plots the estimated β_t for the share of spending paid by cash. The coefficients correspond to the change in cash usage relative to April 2016 (in percentage points) associated with a one percentage point increase in prior cash dependence. The estimates show that cash usage was stable prior to the Demonetization, plummeted by 0.28 percentage point (for each one percentage point increase in prior cash dependence) in November 2016 when the Demonetization took place, and then remained low till the end of our sample period.

Panel (b) plots the estimated β_t for the natural logarithm of spending amount. The coefficients correspond to the proportional change in monthly spending relative to April 2016 (in percentage points) associated with a one percentage point increase in the prior cash dependence. This analysis shows the dynamic pattern of spending and provides another test of the parallel trends assumption underlying our research design. In the seven months prior to the Demonetization, there is little change in spending across households with differential degree of cash dependence. In November 2016, previously cash-reliant households increased their spending relative to the less cash-reliant households; the estimated differential change between the households at the 75$^{\text{th}}$ and 25$^{\text{th}}$ percentiles of prior cash dependence is 6%. The differential change continues to increase till the end of our sample period. The parallel pre-trend implies that spending would have been unlikely to change if not for the Demonetization, reinforcing our claim that the observed increase in spending by previously cash-reliant consumers is likely to capture the causal response to the adoption of digital payments.

5.D Characteristics of Spending Response

So far, we have shown that the Demonetization induces consumers who were previously heavily cash-reliant for supermarket purchases to adopt digital alternatives and increase spending. To provide perspectives on the mechanisms driving this spending response, we exploit the richness of our data to analyze different types of spending, spending variety and shopping intensity, as well as the quantity and price of goods purchased.

5.D.1 Spending by type

We first differentiate food and non-food spending. Columns 1 & 2 of Table 4 report the effect on the probability of positive food and non-food spending, respectively. A coefficient of 0.006 in column 1 implies that an increase of 10 percentage points in the prior cash dependence is associated with a 0.06 percentage point increase in the probability of spending on food products following the Demonetization. The increase is roughly 0.06% of the average probability of 94%. On the contrary, column 2 shows that an increase of 10 percentage points in the prior cash dependence is associated with a 0.63 percentage point increase in the probability of spending on non-food products, or 1.1% of the pre-period level, following the Demonetization. In column 3, the outcome variable is the share of non-food spending in total spending. According to its estimate, an increase of 10 percentage points in the prior cash dependence is associated with a 0.18 percentage point increase, or a 0.82% increase, in the share of non-food spending in total spending, following the Demonetization.

We consider an alternative dichotomy between durable and non-durable purchases and report the corresponding analyses in columns 4–6 of Table 4. A coefficient of 0.013 in column 4 implies that an increase of 10 percentage points in the prior cash dependence is associated with a 0.13 percentage point increase, or a 3% increase, in the probability of durable shopping following the Demonetization. Column 5 shows that an increase of 10 percentage points in the prior cash dependence is associated with an increase of less than 0.01 percentage point in the probability of non-durable spending following the Demonetization. The increase is tiny relative to the average probability of 100%. Column 6 shows that an increase of 10 percentage points in the prior cash dependence is associated with a 0.01 percentage point increase, or a 1.2% increase, in the share of durable shopping in total spending, following the Demonetization.

5.D.2 Spending variety and shopping intensity

We also examine how variety of supermarket spending and shopping intensity respond to the forced switch to digital payments in Table 5. We measure variety of supermarket spending by the number of unique products purchased (product variety, column 1), the number of unique broad categories purchased (broad category variety, column 2), the number of unique product categories purchased (category variety, column 3), and the number of unique stores within the supermarket chain from which a consumer makes purchases (shop variety, column 4). The estimates show that previously cash-reliant consumers increased the variety of their supermarket spending by a statistically significant margin according to all four variety measures as they were forced to switch to digital payments following the Demonetization. We measure shopping intensity by counting the number of shopping trips in a month. In column 5, we find that shopping intensity, as measured by the number of trips, also increased. But the effect is not statistically significant.

5.D.3 Types and prices of products purchased

Lastly, we examine the types and prices of products purchased. The spending data records the name of the products, as well as the product categories. The product name includes the brand and the portion, if applicable. The store classifies all the products into five hierarchical layers of categories. For this analysis, we use the two most granular categorizations. Examples of the second most granular categories include "Cereals - Pulses and Flours," "Fruits," "Vegetables," "Cooking Appliances," and "Infant Underwear & Night Wear." Each of these categories can be further broken down into a few next-level categories. For example, the "Vegetables" category can be broken down into "Local Vegetables" and "Special/Exotic Vegetables." This granular categorization makes the products in the same category more comparable in terms of intrinsic value and therefore makes the quantity purchased and the unit price meaningful.

We conduct the category-level analysis using equation (3) for three outcome variables: the rupee amount spent on the category (Amount), the quantity of goods purchased (Quantity), and the unit price of goods purchased (Unit Price). The results are reported in Table 6. Panel A reports the results using the second most granular definition of categories, and Panel B reports the results using the most granular definition of categories. Under both levels of granularity, we find a positive coefficient for Amount, Quantity, and Unit Price. The effect is strongest for Unit Price: Consumers with a higher prior cash dependence buy more expensive products following the Demonetization.

5.E Heterogeneity

Next, we examine whether different individuals experienced heterogeneous responses to the Demonetization. To this end, we divide the households into ten decile groups based on the level of monthly spending and separately estimate equation (1) for each group. We plot the heterogeneous responses in Figure 4.

The top panel plots the ten decile-specific $\widehat{\beta}$ for the fraction of spending paid by cash as the outcome variable. We find that decile-specific $\widehat{\beta}$ is negative for all decile groups. In addition, there is a clear negative relationship between the forced switch to digital payments and the level of spending. The bottom panel plots the ten decile-specific $\widehat{\beta}$ for the log level of spending as the outcome variable. We find that previously cash-reliant consumers in all decile groups increase their spending following the Demonetization. Moreover, the increase in spending is monotonically decreasing from the lowest spending decile to the highest spending decile.

This analysis demonstrates that the Demonetization induces the strongest switch to digital payments and therefore increases spending the most for consumers with the lowest level of spending.

6 Addressing Identification Challenges

In this section, we address several key concerns with our empirical approach: income shocks, credit supply, suppliers' pricing responses, and consumers' moving to the formal market.

6.A Identifying Concern 1: Income Shocks

One might be concerned about an income shock channel whereby individuals who switch to digital payments due to the Demonetization shock experience positive income shocks and therefore increase their spending. To begin with, the elevated economic uncertainty and reduction in economic activities following the Demonetization render positive income shocks unlikely to occur.[11] The district$\times$time fixed effects we include in our regression specifications also directly control for the time-series fluctuation of the national and regional economic conditions.

[11]The *ex-ante* secrecy and the slow and disorderly replenishment of notes associated with the Demonetization increased economic uncertainty. It is also widely believed that such a policy posed a painful disruption to the economy. For instance, the Conversation commented, "The implementation process faced technical disruptions, leading to severe cash shortages, and the overall poor preparation of the policy led the country into chaos for more than three months." (Source: `http://theconversation.com/the-shock-of-indian-demonetisation-a-failed-attempt-to-formalise-the-economy-93328`). Relatedly, Chodorow-Reich et al. (2019) find that the Demonetization lowered the growth rate of economic activity by at least 2 percentage points in 2016Q4.

A more nuanced income shock explanation involves a re-allocation of (relative) income among individuals of varying exposure to the Demonetization shock. Economic activities in the informal sector, including black market activities, take a hit following the Demonetization as evidenced by the near complete returning of demonetized notes to the RBI.[12] Black market activities are largely cash-based. Recipients of the black money payments in cash do not deposit into banks, as doing so would force them to justify the source of income and bear tax consequences. Instead, they tend to use cash to pay for their purchases. In our setting, they will exhibit a high level of cash dependence and therefore be classified as individuals with high treatment intensity. The contraction in black market activities implies that the income shock experienced by individuals with a higher prior dependence, if exists, is negative and therefore makes us underestimate the true positive impact of digital payments on spending.

To examine whether this conjecture holds in our data, we contrast the effect on households who were likely to engage in black market activities with that on other households. Since we do not directly observe households' source of income, we proxy for black market income with the behavior of paying large receipts with cash in the pre-Demonetization period. Spending the cash on large receipts is a viable way for them to hide their black market income. On the contrary, using cash for large receipts is quite unusual in normal circumstances, given that small receipts tend to be paid by cash as discussed in Section 4.

In the empirical implementation, we define large receipts as receipts whose amount exceeds the 90^{th} percentile (467 rupees[13]) in the size distribution observed from all receipts paid by cash from April 2016 to October 2016. Table 7 reports the estimation results. We find a much muted response by households who were likely to engage in black market activities, consistent with negative income shocks.

[12] According to the RBI's Annual Report 2017-18, 99% of total 500 and 1000 notes in circulation prior to the Demonetization were returned to the RBI, contrary to the earlier expectations that the restrictions on depositing money from unverifiable sources would lead to difficulty in absorbing black money and liquidation of RBI's currency liabilities.

[13] For the sake of comparison, the 75^{th} percentile of all receipts in the full sample, regardless of payment method, is 311.37 rupees.

6.B Identifying Concern 2: Credit Supply

Credit cards, one of the digital alternatives to cash payment, allow consumers to borrow to spend. Such a feature relaxes the budget constraint and therefore increases the level of optimal spending. If banks increase their supply of credit card lending, we might also observe an increase in spending.

In the aggregate, bank credit declined by at least 2 percentage points in 2016Q4 despite an inflow of deposits to the banking sector (Chodorow-Reich et al., 2019). In our context of supermarket spending, credit card usage remained low throughout the sample period; the decline in cash usage is mostly compensated by the uptick in debit card usage (Figure 1). Given the aggregate credit contraction and the low usage rate in our context, it is unlikely that credit supply is driving our results.

Can banks increase credit supply targeted to consumers who relied primarily on cash and thus relax their budget constraints more relative to other consumers? Drawing on the insights from the literature on credit history and access to credit, we expect banks to increase their supply of consumer credit to existing credit card users, who are not likely to be consumers who relied primarily on cash for supermarket spending prior to the Demonetization. This conjecture is supported by the result in Table 2 that high prior cash dependence leads to a significantly lower credit card usage, albeit small in magnitude, following the Demonetization. A positive relationship between credit history and access to credit, if anything, would lead us to underestimate the positive effect of digital payments on spending.

To further investigate whether there is a shift in credit supply following the Demonetization and the extent to which this credit supply channel at work affects our results, we re-estimate equation (1) for three subsamples based on credit card usage: existing users, defined as consumers who used credit cards before the Demonetization; new users, defined as consumers who started to use credit cards following the Demonetization; and non-users, defined as consumers who never used any credit card in the sample period. The results are reported in Table 8.

The spending response associated with prior cash dependence has a smaller magnitude in the sample of existing users (column 2) than in the full sample (column 1). Existing users are also characterized by a markedly lower prior cash dependence. Since existing credit card users had already adopted digital payments to a large extent, it is not surprising that they do not appear to be affected by the Demonetization as much. Among existing credit card users, the credit card usage prior to the Demonetization can be viewed as a proxy for the strength of the relationship with banks. If credit supply indeed increased following the Demonetization, it would have increased more for consumers with a stronger relationship with banks. To empirically test it, we add an interaction term of prior credit card usage and the post-Demonetization indicator to the baseline specification (column 3). The coefficient of this interaction term is positive, suggesting that an increase in credit supply contributes to the increase in spending for consumers with a strong relationship with banks.

The spending response associated with prior cash dependence is larger in the sample of new users (column 4). Note that the post-Demonetization spending by new users was influenced by their newly obtained credit card borrowing capacity. Therefore, the difference in the spending response of new users relative to that of non-users can be viewed as an estimate of the added effect of credit supply.

The spending response associated with prior cash dependence in the sample of non-users (column 5) is almost identical to the full-sample estimate. The comparison of sample sizes shows that the majority of consumers in our sample are non-users — 88% in terms of individual-monthly observations.

Taken together, the results show that an increase in credit supply affects a small fraction of consumers, at best, empirically. Our main results are not driven by the potential confounder of credit supply response.

6.C Identifying Concern 3: Supplier's Pricing Response

We next consider if the effect of digital payments on spending can be explained by an increase in product prices. If product suppliers, either the manufacturers or the supermarket chain, anticipate consumers to become less price sensitive following the adoption of digital payments, they could potentially take advantage of this by increasing their mark-up.

To begin with, there is no evidence of a general increase in price level following the Demonetization. The year-over-year growth rate of India's Consumer Price Index (CPI) monotonically declined from 6.068% in June 2016 to 3.167% in January 2017. Consistent with the national CPI, the increase in the average price level across all products sold in the supermarket chain around the time when the Demonetization was announced is very modest (Online Appendix Figure OA.3). The district×time fixed effects we include in our regression specifications also directly control for the time-series fluctuation of the general price level. Therefore, an increase in mark-up at the aggregate level, which is modest at best, does not explain the cross-sectional pattern that we have documented here.

Thus, for the increase in mark-up to qualify as an explanation for our results, it has to be the case that the product mark-up is somehow larger for consumers with a high prior cash dependence. As suppliers cannot achieve perfect price discrimination, that is, they cannot directly charge different consumers different prices for the same product at the same store and at the same time, this alternative explanation must involve consumers with different prior cash dependence having different spending profiles.

To directly test this possibility, we construct a measure of exposure to cash-dependent consumers for each product by taking the average of consumer-level reliance on cash, weighted by the spending amount from April 2016 to October 2016. We sort all products into "high exposure" (above the median) and "low exposure" (below the median) groups. We then examine whether the price of "high exposure" products increases faster relative to "low exposure" products using the following regression:

$$y_{i,j,t} = \mu_i + \pi_j + \sum_{t \neq 0} \beta_t \mathbb{1}_t + \sum_{t \neq 0} \gamma_t \left(\mathbb{1}_t \times \mathbb{1} \left(HighExposure_i \right) \right) + \varepsilon_{i,j,t} \tag{4}$$

The dependent variable $y_{i,j,t}$ is the log of the mean transaction price of product i in store j on day t. $\mathbb{1}_t$ are monthly indicators; month 0 corresponds to November 2016 when the Demonetization took place and is the omitted baseline group. In this log-linear specification, the exponentiated coefficient for the interaction between month t and the high exposure indicator γ_t corresponds to the incremental change in the price level of month t (normalized by the price level in November 2016) of "high exposure" products relative to "low exposure" products. We plot the exponentiated γ_t in Figure 5. We find no evidence that high-exposure products experienced a larger price increase than low-exposure products.

6.D Identifying Concern 4: Moving Purchases to the Formal Market

Another concern for our identification strategy arises from the possible shift from unobserved purchases to purchases recorded to our data. If cash users used to buy grocery from informal markets, such as wet markets and street stalls, and moved their purchases to the supermarket after the Demonetization, they would have a higher spending response as captured by the data. This possibility would lead to an upward bias of the estimated impact.

Our findings are unlikely to be attributable to the purchase shift for two reasons. First, new consumers that arrived after the Demonetization are excluded from our analysis. Our estimation is not affected by the shift from informal markets to the supermarket in the form of newly arrived consumers. Second, if a shift of purchases from informal markets to the supermarket among existing supermarket consumers is driving our results, the observed spending response should concentrate on the types of products commonly available in informal markets such as fresh produce and other non-durable goods. However, we find that the spending response is markedly higher in non-food spending and durable spending relative to food spending and non-durable spending in section 5.D.

We also test for heterogenous shifts of purchases from informal markets to the supermarkets across consumers. We hypothesize that consumers who mainly bought non-food goods in the supermarket chain are likely to be those who are shifting their food purchases and therefore they should exhibit a higher spending response following the Demonetization.

To test this, we divide all individuals into two groups based on whether the share of food spending in the seven months prior to the Demonetization reaches the median level (88%, Table 1). We examine the fraction of spending paid by cash, log level of total spending, and the share of food spending for the two groups separately and report the estimates in Table 9. Although the switch to digital payments is roughly equalized between the two groups, the spending response is higher among individuals with above-the-median prior food spending, opposite of what the heterogeneous shifts of purchase would predict. The increase in the share of food spending observed among individuals with below-the-median prior food spending lends some support for a shift of purchases from informal markets to the supermarket. On the contrary, individuals with above-the-median prior food spending increased their spending and at the same time decreased their share of food spending, implying that their spending response is not driven by the shift of purchases from informal markets to the supermarket.

7 Additional Analyses and Discussions on the Underlying Mechanisms

Thus far, we have documented that the usage of digital payments increased sharply following the Demonetization and as a result, households who previously relied on cash payment increased their supermarket spending. This finding rejects the prediction of monetary neutrality that consumer valuation of products and services is independent of how money is represented.

Payment instruments have distinctive features that can influence consumer behaviors. Our finding is consistent with two channels. The first involves the *transaction costs* associated with using cash, such as the storage cost, the time costs of traveling to a bank branch or an ATM to withdraw cash (Bachas et al., 2018), and the risk of cash theft (Economides and Jeziorski, 2017; Rogoff, 2014). Using digital payment instruments for purchases can save these transaction costs and hence increase consumer spending, especially spending by those mostly affected by the transaction costs. The second channel involves the various behavioral implications associated with cash payment being effortful, instant, and memorable. The behavioral channel can exhibit several variants. One variant states that the effortful and costly cash payment can serve as a decision point for consumers to evaluate their expenses, while card and mobile payments remove the decision point and hence make spending easier. A different variant is described as *"pain of paying"* or *payment transparency* (Prelec and Loewenstein, 1998; Soman, 2003; Raghubir and Srivastava, 2008). Cash payment is perceived to be painful because the consumer has to physically endure the act of parting with their hard-earned money. On the contrary, card and mobile payments are perceived to be less painful as no money actually exchanges hands. We refer to these different variants of the behavioral channel collectively as the "salience" channel. In this section, we analyze which channel, transaction costs or saliance, qualifies as a more plausible explanation for our empirical finding.

To do so, we exploit the differential impact of salience of cash on offline and online purchases and compare consumer spending behaviors in the supermarket with an online grocery store. Online purchases of physical goods such as grocery products are characterized by a time lag between the purchase decision and the delivery of goods. Paying with cash for online shopping takes the form of cash on delivery, which is not fulfilled until the delivery takes place. At the time of the purchase decision, both cash payment and digital payments involve no physical exchange of money between hands. Therefore, paying for an online purchase with cash invokes either the decision point or the pain of paying to an lesser extent than paying for an offline purchase with cash. Crucially, the transaction costs associated with cash apply equally to online and offline shopping.

We apply our core empirical approach based on the cross-consumer variation of cash dependence prior to the Demonetization to study payment choice and consumer spending in the online grocery setting. We use the data from a large online grocery retailer in India for a period from January 2016 to April 2019 and construct individual-monthly observations as in our main analysis.[14] We estimate equation (1) to examine how payment choice and spending changes for individuals with different levels of prior cash dependence following the Demonetization conditional on the inclusion of individual fixed effects and district×time fixed effects.

Table 10 reports the estimates obtained from the online grocery retailer data. The sample period in columns 1 & 2 (2016:01–2017:09) covers eleven months following the Demonetization same as in our main analysis using the supermarket data. Columns 3 & 4 report the results obtained from the full sample period (2016:01–2019:04). Regardless of the sample period, we find that the forced switch to digital payments by previously cash-reliant individuals is stronger in the online retailer panel. On the contrary, the spending response is much muted. The estimated proportional increase in spending is 0.4 to 0.7 percentage points for every ten additional percentage points of prior cash dependence, or one-fifth of the effect found in the supermarket panel (column 6, Table 2).

The difference in estimates for the spending response between the two panels suggests that the large spending response we observe in the supermarket panel is likely to reflect the behavioral forces as opposed to the transaction costs.

8 Conclusion

Digital payment instruments are faster and more convenient ways to pay for purchases of goods and services. They are also seen as more secure, with less chance of a consumer losing money in the street or being pick-pocketed. Besides, all payments can be traced, so it is more difficult for a consumer to fall victim to fraud. From the perspective of financial development, digital payments can also facilitate better financial intermediation. Digital payments can, however, induce over-spending

[14] Additional details for sample construction and variable definitions can be found in Online Appendix A.

due to its lower salience than cash. Card users can go for weeks or longer without checking how much they have spent. When households "tap and go" using cards or mobile payments, it is easy for them to become complacent and over-spend.

We study the real effects of digital payments adoption in the unique episode of the 2016 Demonetization in India. This policy, which removed a large portion of currency-in-circulation from legal tender overnight, forced consumers to switch from cash to digital payments. Using a difference-in-differences empirical approach that exploits the cross-consumer variation in cash dependence, we find that digital payments lead to a substantial increase in consumer spending.

In interpreting the causality implications, we argue that income shocks, credit supply, supplier's pricing responses, and shifting purchases to the formal market are unlikely to explain our results. Together with the strong evidence that consumers who were forced to switch to digital payments purchased more expensive goods, our analysis suggests substantial over-spending induced by digital payments.

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Figure 1: **Demonetization and Payment Modes**

This figure demonstrates the influence of the sudden Demonetization policy on payment methods.

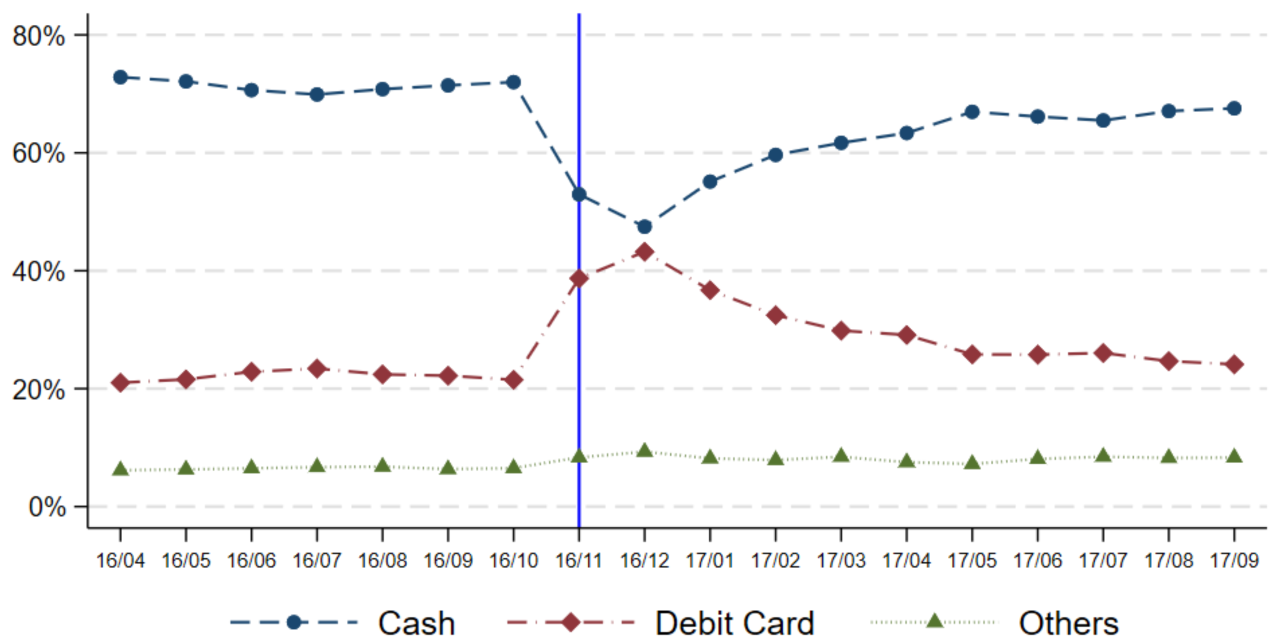
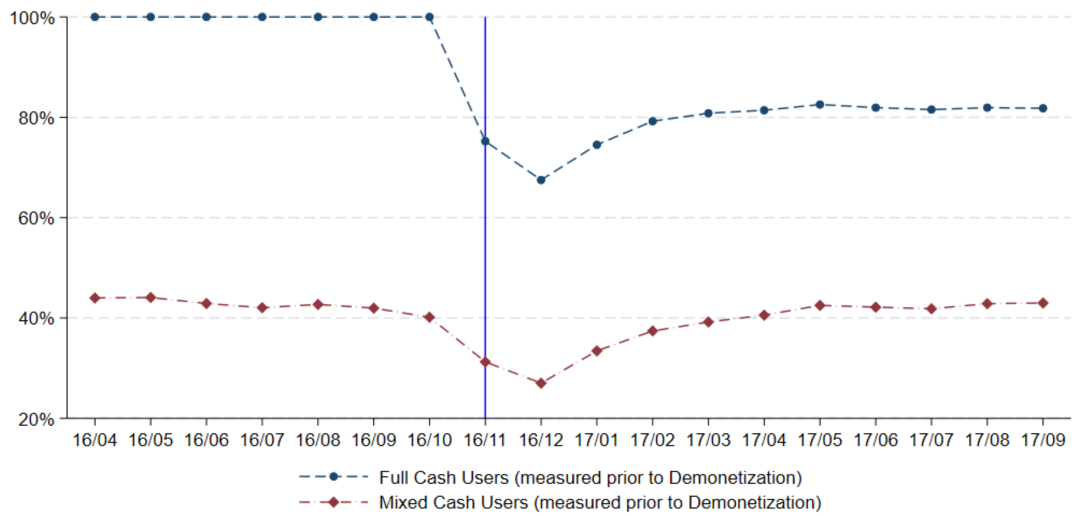


Figure 2: **Cash Usage and Spending Response to Demonetization (Two-Group Comparison)**

This figure plots the average cash usage and log spending for full cash users and mixed users over time. For each consumer in the sample, the prior cash dependence is calculated as the average share of spending paid by cash from April 2016 to October 2016. The group of full cash users comprises the consumers whose prior cash dependence is 100%; the group of mixed cash users comprises the consumers whose prior cash dependence is lower than 100%.

(a) Cash usage over time



(b) Log spending amount over time

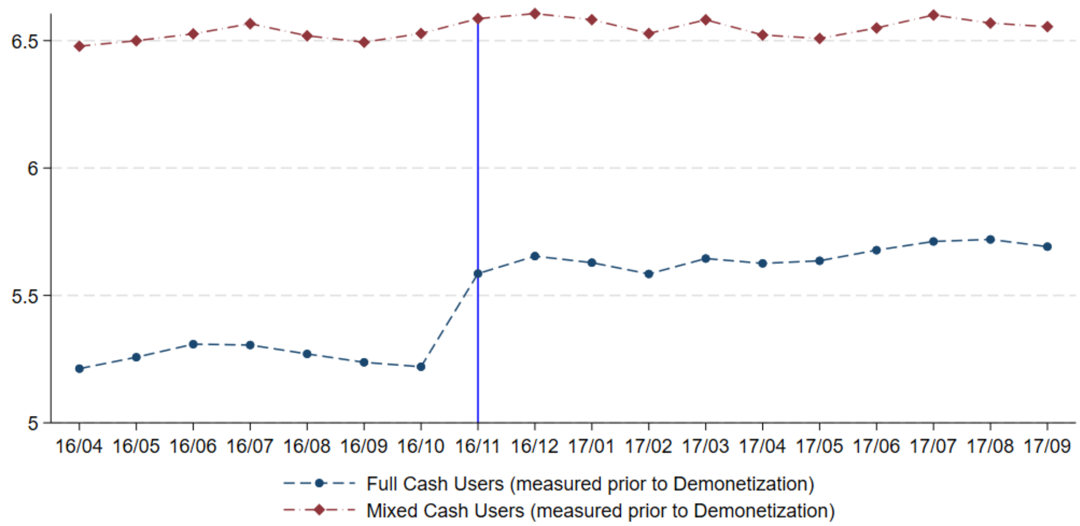
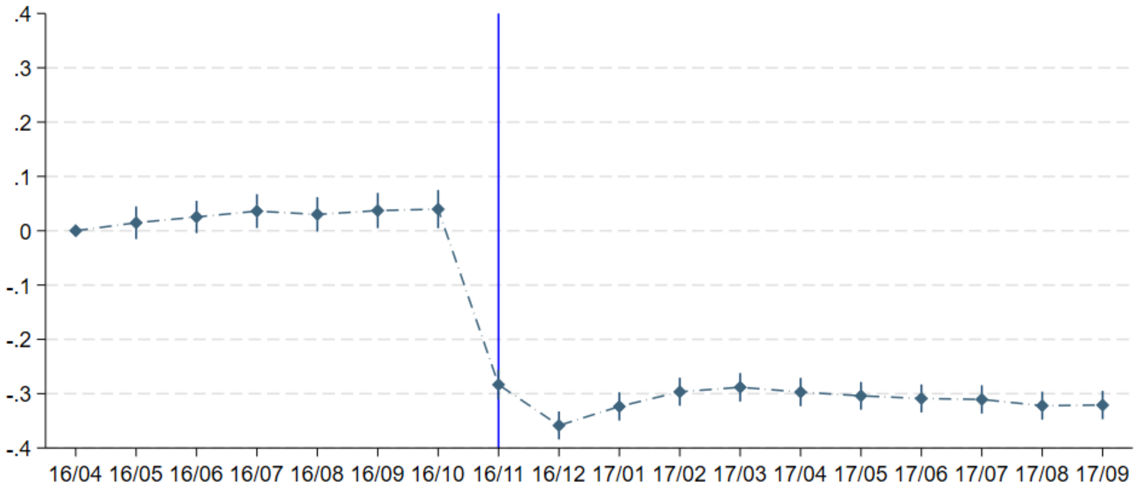


Figure 3: **Dynamic effects of digital payments on spending**

This figure plots the entire path of coefficients β_t of the fraction of spending paid by cash and the log level of spending as estimated from equation (2). The *x-axis* denotes the months (2016:04–2017:09). Demonetization took place in November 2016. In the dynamic specification, April 2016 is the omitted baseline group. The *y-axis* corresponds to the change in cash usage (the proportional change in spending) relative to the benchmark level measured in April 2016 in panel a (panel b).

(a) Cash usage



(b) Log spending

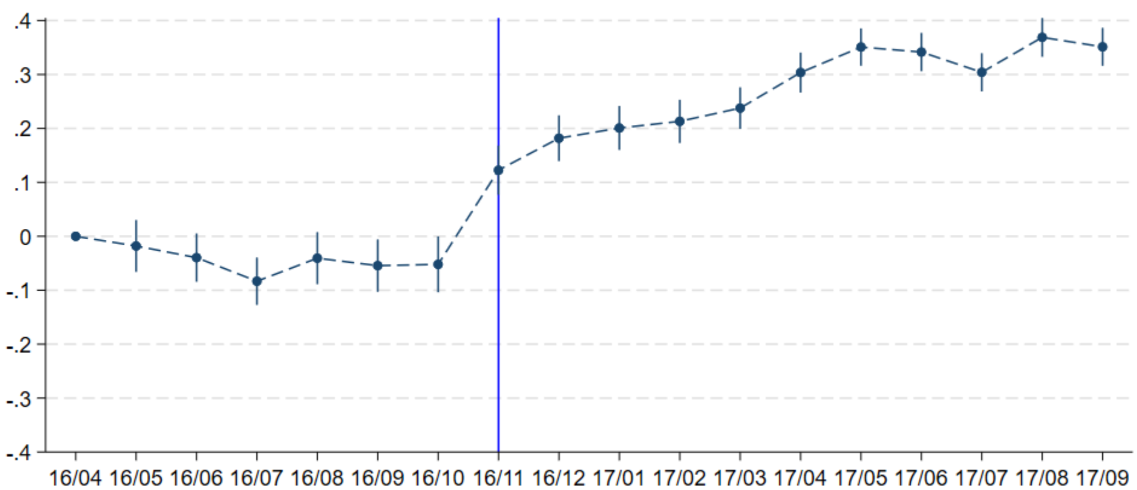


Figure 4: **Heterogeneous switch to digital payments and its effect on spending**

This figure plots the decile-specific $\widehat{\beta}$ as estimated from equation (1) in the subsample of each of the ten decile groups based on the level of monthly spending. The data are at the individual-month level (2016:04–2017:09).

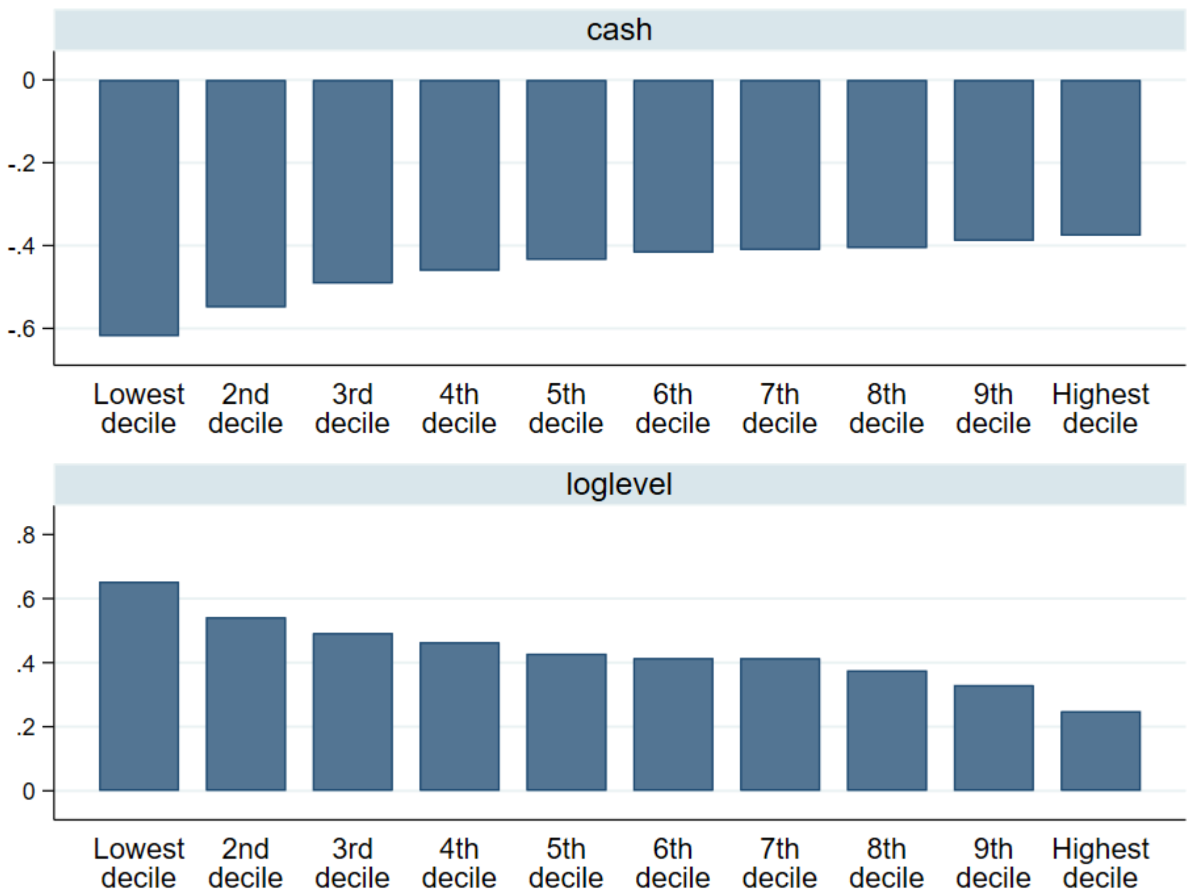


Figure 5: **Price level by pre-Demonetization exposure to cash-dependent consumers**

This figure shows the price level of products sold by the supermarket chain, sorted by their pre-Demonetization exposure to cash-dependent individuals, in our sample at a monthly frequency. The figure plots the exponentiated coefficients γ_t and the associated 95% confidence intervals as estimated from equation (4). High (low) exposure products refer to products with above-the-median (below-the-median) exposure to cash-dependent consumers, calculated as the spending-amount-weighted average of consumer-level reliance on cash in the period from April 2016 to October 2016. In this log-linear specification, the exponentiated coefficient for the interaction between month t and the high exposure indicator corresponds to the incremental change in the price level of month t (normalized by the price level in November 2016) of "high exposure" products relative to "low exposure" products.

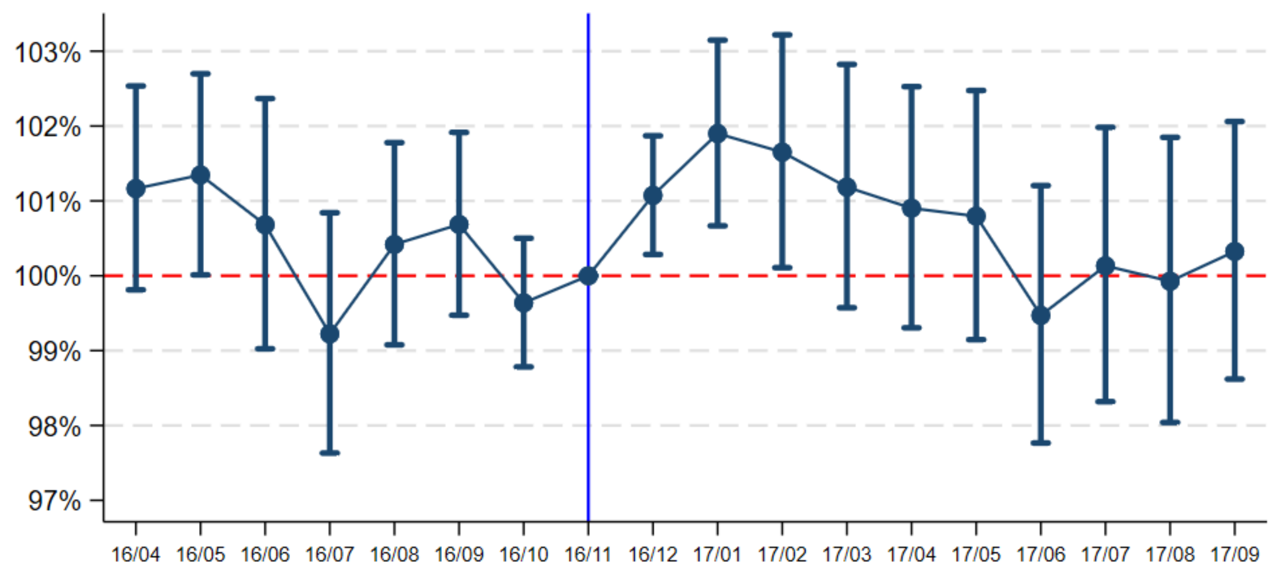


Table 1: **Summary statistics**

This table reports the summary statistics of our sample in the main analysis—individual consumers that started shopping at a large Indian supermarket chain before November 2016 and remained as customers afterwards. The sample period of our main analysis is from April 2016 to September 2017. Additional details for sample construction and variable definitions can be found in Online Appendix A. Except for payment instruments' respective shares in panel (a), we first calculate the within-individual average of each variable in the seven months prior to the Demonetization (2016:04–2016:10) and then report the cross-sectional mean, standard deviation, and median. For the variables in panel (a), we report the cross-sectional summary statistics of within-individual averages for the 2016:04–2016:10 and 2016:11–2017:09 periods separately. The monetary amount is the local currency Indian rupee (INR) and 1 USD = 66.7 INR as of October 2016.

	Mean	Std. Dev.	25%	50%	75%
Fraction of payment mode in spending					
Cash payment (2016:04–2016:10)	0.72	0.39	0.45	1	1
Cash payment (2016:11–2017:09)	0.60	0.40	0.19	0.71	1
Debit cards (2016:04–2016:10)	0.22	0.35	0	0	0.38
Debit cards (2016:11–2017:09)	0.32	0.37	0	0.12	0.61
Mobile payment (2016:04–2016:10)	0.0021	0.036	0	0	0
Mobile payment (2016:11–2017:09)	0.0045	0.048	0	0	0
Credit cards (2016:04–2016:10)	0.0069	0.061	0	0	0
Credit cards (2016:11–2017:09)	0.030	0.13	0	0	0
Total spending and its composition:					
Monthly spending (Indian rupees)	830.7	12515.7	174.4	400	911.6
Share of food spending	0.78	0.28	0.65	0.88	1
Share of non-food spending	0.22	0.28	0	0.12	0.35
Share of durable spending	0.0085	0.056	0	0	0
Share of non-durable spending	0.99	0.056	1	1	1
Indicator for food spending > 0	0.94	0.21	1	1	1
Indicator for non-food spending > 0	0.56	0.42	0	0.67	1
Indicator for durable spending > 0	0.044	0.16	0	0	0
Indicator for non-durable spending > 0	1.00	0.032	1	1	1
Spending variety and shopping intensity:					
Product variety	10.3	11.8	3	6.33	13
Broad category variety	2.31	1.06	1.50	2	3
Category variety	5.34	4.45	2	4	7
Shop variety	1.02	0.13	1	1	1
Number of shopping trips	1.71	1.55	1	1	2
Number of households	924,753				

Table 2: **Forced switch to digital payments and its effect on spending**

This table shows the effect of the forced switch to digital payments due to the Demonetization on payment methods and spending (equation (1)). The data are at the individual-month level (2016:04–2017:09). Outcome variables include the fraction of spending paid by cash, debit cards, mobile payments, and credit cards as well as the absolute and log levels of spending. Prior cash dependence is the average share of spending paid by cash from April 2016 to October 2016 for each consumer. Post is an indicator for post-Demonetization months. Fixed effects are denoted at the bottom. Standard errors are clustered at individual level and at month level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Fraction of payment mode in spending				Spending	
	(1) Cash payment	(2) Debit card	(3) Mobile payment	(4) Credit card	(5) Level	(6) Log
PriorCashDependence × Post	-0.338***	0.296***	0.001**	-0.019***	239.322***	0.307***
	[-39.20]	[42.01]	[2.27]	[-3.30]	[3.11]	[12.61]
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
District × Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.622	0.566	0.350	0.403	0.436	0.586
No. of Observations	6,561,580	6,561,580	6,561,580	6,561,580	6,561,580	6,561,580

Table 3: **Digital payments and spending (subsample analyses)**

This table shows the subsample analyses for the effect of the forced switch to digital payments due to the Demonetization on payment methods and spending (equation (1)). The data are at the individual-month level (2016:04–2017:09). In the first subsample analysis (columns 1–3), we exclude full cash users prior to the Demonetization. In the second subsample analysis (columns 4–6), we exclude the first three months following the Demonetization announcement (November 2016, December 2016, and January 2017). Outcome variables include the fraction of spending paid by cash as well as the absolute and log levels of spending. Prior cash dependence is the average share of spending paid by cash from April 2016 to October 2016 for each consumer. Post is an indicator for post-Demonetization months. Fixed effects are denoted at the bottom. Standard errors are clustered at individual level and at month level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Excluding full cash users			Excluding Nov 2016 to Jan 2017		
	(1) Cash payment	(2) Spending (level)	(3) Spending (log)	(4) Cash payment	(5) Spending (level)	(6) Spending (log)
PriorCashDependence × Post	-0.413***	375.665	0.177***	-0.330***	289.047***	0.345***
	[-36.67]	[1.38]	[9.23]	[-43.20]	[3.11]	[17.55]
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
District × Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.518	0.436	0.539	0.636	0.447	0.596
No. of Observations	3,720,539	3,720,539	3,720,539	5,427,290	5,427,290	5,427,290

Table 4: **Digital payments and different components of spending**

This table shows the effect of the forced switch to digital payments due to the Demonetization on different components of spending (equation (1)). The data are at the individual-month level (2016:04–2017:09). In columns 1–3, we differentiate food and non-food spending and examine three outcome variables, namely, the probability of having positive food spending, the probability of having positive non-food spending, and the share of non-food spending in total spending. In columns 4–6, we differentiate durable and non-durable spending and examine three outcome variables, namely, the probability of having positive durable spending, the probability of having positive non-durable spending, and the share of durable spending in total spending. Prior cash dependence is the average share of spending paid by cash from April 2016 to October 2016 for each consumer. Post is an indicator for post-Demonetization months. Fixed effects are denoted at the bottom. Standard errors are clustered at individual level and at month level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Differentiate food & non-food spending			Differentiate durable & non-durable spending		
	(1)	(2)	(3)	(4)	(5)	(6)
	Food spending > 0	Non-food spending > 0	Non-food spending share	Durable spending > 0	Non-durable spending > 0	Durable spending share
PriorCashDependence × Post	0.006***	0.063***	0.018***	0.013***	0.000	0.001***
	[4.65]	[16.85]	[9.12]	[8.59]	[1.54]	[5.76]
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
District × Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.345	0.443	0.437	0.243	0.251	0.277
No. of Observations	6,561,580	6,561,580	6,561,580	6,561,580	6,561,580	6,561,580

Table 5: **Digital payments and shopping variety and intensity**

This table shows the effect of the forced switch to digital payments due to the Demonetization on shopping variety and intensity measures (equation (1)). The data are at the individual-month level (2016:04–2017:09). Product/broad category/category/shop variety is the number of unique products/broad category/categories/shops that a household purchases in the given month. Number of trips is the number of shopping trips, defined as unique shop-date pairs, a household engages in a given month. Prior cash dependence is the average share of spending paid by cash from April 2016 to October 2016 for each consumer. Post is an indicator for post-Demonetization months. Fixed effects are denoted at the bottom. Standard errors are clustered at individual level and at month level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	(1)	(2)	(3)	(4)	(5)
	Product variety	Broad category variety	Category variety	Shop variety	No. of trips
PriorCashDependence × Post	2.002***	0.212***	0.975***	0.002*	0.027
	[7.11]	[14.39]	[11.99]	[2.07]	[0.85]
Individual FEs	Yes	Yes	Yes	Yes	Yes
District × Time FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.650	0.531	0.634	0.523	0.594
No. of Observations	6,561,580	6,561,580	6,561,580	6,561,580	6,561,580

Table 6: **Effect of digital payments on spending behaviors in granular product categories**

This table estimates the effect of the forced switch to digital payments due to the Demonetization on category-level spending (equation (3)). Panel A reports the results using the second most granular definition of categories and Panel B reports the results using the most granular definition of categories. The data are at the individual-product category-month level (2016:04–2017:09). Amount, Quantity, and Unit Price are the spending amount in rupees, the quantity of goods purchased, and the unit price of goods purchased by a given consumer on a given category in a given month, respectively. Prior cash dependence is the average share of spending paid by cash from April 2016 to October 2016 for each consumer. Post is an indicator for post-Demonetization months. Fixed effects are denoted at the bottom. Standard errors are clustered at individual level and at month level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

Panel A: Results using the second most granular definition of categories

	(1) Amount	(2) Quantity	(3) Unit Price
PriorCashDependence × Post	28.153	0.494	1.381***
	[1.34]	[1.21]	[12.10]
Individual × Category FEs	Yes	Yes	Yes
District × Category × Time FEs	Yes	Yes	Yes
R^2	0.410	0.355	0.680
No. of Observations	42,858,979	42,858,979	42,858,979

Panel B: Results using the most granular definition of categories

	(1) Amount	(2) Quantity	(3) Unit Price
PriorCashDependence × Post	20.372	0.367	0.829***
	[1.25]	[1.16]	[8.28]
Individual × Category FEs	Yes	Yes	Yes
District × Category × Time FEs	Yes	Yes	Yes
R^2	0.399	0.385	0.771
No. of Observations	54,603,502	54,603,502	54,603,502

Table 7: **Is increased spending driven by change in income?**

This table estimates the effect of the forced switch to digital payments due to the Demonetization on payment methods and spending for two subsamples classified by the behavior of paying large receipts with cash prior to the Demonetization, which can be viewed as a proxy for getting income from black money activities. Large receipts are defined as receipts whose amount exceeds the 90^{th} percentile (467 rupees) in the distribution of receipt size from April 2016 to October 2016. The data are at the individual-month level (2016:04–2017:09). Cash usage, Spending, and Log(spending) are the fraction of spending paid by cash, the amount of spending, and the log amount of spending by a given consumer in a given month. Post is an indicator for post-Demonetization months. Fixed effects are denoted at the bottom. Standard errors are clustered at individual level and at month level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Did not use cash for large bills pre-Demo			Used cash for large bills pre-Demo		
	(1) Cash usage	(2) Spending	(3) Log(spending)	(4) Cash usage	(5) Spending	(6) Log(spending)
PriorCashDependence × Post	-0.356***	240.412***	0.537***	-0.240***	243.569**	0.015
	[-46.44]	[9.90]	[18.57]	[-21.54]	[2.89]	[0.55]
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
District × Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.659	0.593	0.566	0.546	0.437	0.486
No. of Observations	3,950,372	3,950,372	3,950,372	2,611,208	2,611,208	2,611,208

Table 8: **Is increased spending driven by credit supply shock?**

This table estimates the effect of the forced switch to digital payments due to the Demonetization on spending for three subsamples based on credit card usage: existing users, defined as consumers who used credit card before the Demonetization; non-users, defined as consumers who never used any credit card in the sample period; and new users, defined as consumers who started to use credit cards following the Demonetization. The data are at the individual-month level (2016:04–2017:09). Log(spending) is the log amount of spending by a given consumer in a given month. Post is an indicator for post-Demonetization months. Fixed effects are denoted at the bottom. Standard errors are clustered at individual level and at month level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Log(spending)				
	Full	Existing users		New users	Non-users
	(1)	(2)	(3)	(4)	(5)
PriorCashDependence × Post	0.307***	0.241***	0.260***	0.448***	0.311***
	[12.61]	[8.71]	[8.75]	[18.06]	[12.44]
PriorCreditDependence × Post			0.074**		
			[2.37]		
Individual FEs	Yes	Yes	Yes	Yes	Yes
District × Time FEs	Yes	Yes	Yes	Yes	Yes
R^2	0.586	0.520	0.520	0.505	0.587
No. of Observations	6,561,580	240,191	240,191	551,031	5,770,358

Table 9: **Is increased spending driven by the shift in purchases from informal markets to the supermarket?**

This table estimates the effect of the forced switch to digital payments due to the Demonetization on payment methods and spending. The data are at the individual-month level (2016:04–2017:09). Cash usage is the fraction of spending paid by cash. Post is an indicator for post-Demonetization months. Fixed effects are denoted at the bottom. Standard errors are clustered at individual level and at month level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Pre-Demonetization food spending share is below median (88%)			Pre-Demonetization food spending share is above median (88%)		
	(1)	(2)	(3)	(4)	(5)	(6)
	Cash payment	Spending (log)	Food spending share	Cash payment	Spending (log)	Food spending share
PriorCashDependence × Post	-0.354***	0.207***	0.043***	-0.332***	0.349***	-0.019***
	[-35.58]	[10.08]	[13.36]	[-39.80]	[13.46]	[-19.43]
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes
District × Time FEs	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.608	0.564	0.366	0.629	0.562	0.322
No. of Observations	3,635,392	3,635,392	3,635,392	2,926,188	2,926,188	2,926,188

Table 10: **Forced switch to digital payments and its effect on spending**

This table shows the effect of the forced switch to digital payments due to the Demonetization on payment methods and spending (equation (1)). The data are at the individual-month level. Outcome variables include the fraction of spending paid by cash and the log level of spending. Prior cash dependence is the average share of spending paid by cash from January 2016 to October 2016 for each consumer. Post is an indicator for post-Demonetization months. Fixed effects are denoted at the bottom. Standard errors are clustered at individual level and at month level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Sample: 2016:01–2017:09		Sample: 2016:01–2019:04	
	(1) Cash payment	(2) Log spending	(3) Cash payment	(4) Log spending
PriorCashDependence × Post	-0.522***	0.041***	-0.577***	0.073***
	[-33.97]	[3.30]	[-40.77]	[6.10]
Individual FEs	Yes	Yes	Yes	Yes
District × Time FEs	Yes	Yes	Yes	Yes
R^2	0.651	0.559	0.624	0.525
No. of Observations	209,391	209,391	398,038	398,038

Online appendix

This appendix contains supplementary material, tables, and figures.

A Sample construction and variable definitions

A.1 Supermarket data

The anonymized transaction-level data from a large Indian supermarket chain used in the main analysis of the paper comprise all purchases in 171 stores in twenty-one districts of five states/union territories from April 2016 to September 2017. 80% of purchases involve the use of a loyalty card and therefore can be linked to individual consumers, consistent with the magnitude reported by Hastings and Shapiro (2018). We exclude from our analysis the spending transactions that cannot be linked to individual consumers.

We observe 144.1 million product purchases made on 24.4 million purchase occasions by 4,237,728 households from April 2016 to September 2017. To ensure that the household-level changes in payment choice and spending following the Demonetization are well-defined, we restrict the sample to households that started shopping at this chain before November 2016 and remained as customers afterwards. Our panel contains a total of 924,754 households.

For each product purchased, we observe the quantity, the price (both the listing price and the actual price paid), the product code, a text description of the product, and the product's location within a taxonomy which involves five hierarchical layers of product categories. Using the supermarket's taxonomy, we decompose all products purchased into food products and non-food products. We also consider an alternative dichotomy between durable and non-durable products, based on whether a given product can generally be used for more than one year. The majority of goods sold in the supermarket chain are non-durable, with the exception of furniture, electronics, home appliances, home decor, books & audio and video products, crockery, cooking ware, utensils, sports equipment, and luggage. Non-durable products include all food products as well as health & beauty and household products.

We aggregate the data to the individual-month level. We calculate each individual's total monthly spending, the fraction of spending paid by each of the payment instruments, as well as the share of food, non-food, durable, and non-durable spending in total spending. We also calculate indicators for whether an individual has positive food, non-food, durable, and non-durable spending in a given month, respectively. We measure the variety of supermarket spending by the number of unique products purchased, the number of unique broad categories purchased, the number of unique product categories purchased, and the number of unique stores within the supermarket chain from which a consumer makes purchases. We measure shopping intensity by counting the number of shopping trips in a month, where a trip is defined as a purchase from a given store on a given day.[15]

A.2 Online grocery retailer data

In Section 7 of the paper, we use the anonymized transaction-level data from a large online grocery retailer to study how the Demonetization affects payment choice and the level of spending in the online grocery setting.

The data comprise all purchases in six cities in India from January 2016 to April 2019 and contain anonymized consumer identifiers. As in our main analysis using the supermarket data, we restrict the sample to households that started shopping at this online store before November 2016 and remained as customers afterwards.

As in our main analysis using the supermarket data, we exploit the cross-sectional variation of cash dependence prior to the Demonetization at the individual consumer level to estimate the forced switch to digital payments and the associated spending response. For every individual in the online grocery retailer data, we calculate the prior cash dependence by taking the average share of spending paid by cash from January 2016 to October 2016.

B Additional Discussion of Empirical Approach

The baseline panel regression equation (1) includes both individual fixed effects μ_i and district$\times$time fixed effects $\pi_{d,t}$. The inclusion of the district$\times$time fixed effects ensures that the estimates do not reflect the impact of district-specific currency supply shocks.

To see the effect of these fixed effects, we examine the correlation between district-level cash usage and spending. We calculate the average cash usage and log spending for each district in each month. Panel (a) of Figure OA.1 plots the change of average log spending from October 2016 to November 2016 against the change of

[15]In other words, if a household makes two purchases from two separate stores on a given day, we will count these purchases as two shopping trips. The same applies if this household makes two purchases in the same store on two separate days.

average cash usage. Districts that experienced a larger drop in cash usage exhibit a higher change in spending.

In panel (b), we first de-mean the raw level of individual-level cash usage and log spending with respect to the individual fixed effects to calculate “net” measures before taking the average for each district in each month. We plot the resulting district-level changes in panel (b) and find a similar negative correlation between cash usage and spending.

As the district-level change in cash usage may reflect the currency supply shocks (Chodorow-Reich et al., 2019), availability of cash is a potential omitted variable that can bias our estimate of β in equation (1) upward unless the district-level currency supply shocks are controlled for. The inclusion of the district$\times$time fixed effects removes all impacts of district-level time-varying factors including the currency supply shocks.

C Evidence for Spending Increase Induced by Digital Payments

C.1 Multi-group analysis of unconditional patterns

Figure OA.2 plots between April 2016 to September 2017 for consumers divided into 10 evenly-spaced groups of prior cash dependence, defined as the average share of spending paid by cash from April 2016 to October 2016. This calendar time heatmap is analogous to the traditional two-group calendar time graph commonly used in a difference-in-differences research design, but allows us to visually present the time-series patterns for many more groups. In all three graphs, columns correspond to months and rows correspond to groups of consumers evenly sorted by prior cash dependence. Each cell’s shading corresponds to a within-row average level of a key outcome variable—the share of spending paid by cash in panel (a) and the natural logarithm of spending amount in panel (b).

These heatmap figures lead to three conclusions. First, cash usage was stable for every group before the Demonetization. The average cash usage during this period likely reflects the equilibrium choice for payment method in the steady-state absent from a cash shortage such as the Demonetization. The stability lends support to our approach of taking this prior cash dependence as a measure of exposure to the Demonetization. More importantly, every sequence of consecutive months in the pre-period lends credence to our research design’s core identification assumption of parallel trends. The same is true when we look at spending as the outcome variable.

Second, the smoothly decreasing cash usage, or equivalently the smoothly increasing digital payment usage, in November 2016 shows the switch to digital payments is monotone in the pre-determined exposure and not driven by a few outlier consumers or consumer groups. Third, neither cash usage nor spending appears to reverse back to pre-Demonetization levels in the ten months following the Demonetization despite replenishment of the demonetized notes. The data do not indicate a sharp reversal of the spending response.

C.2 Additional regression results

We also decompose total spending by payment methods. Table OA.1 reports the results for the level of spending by instrument, both in absolute rupee value and in a transformed form, as the outcome variable. Because of the extremely limited adoption of digital payments before the Demonetization, taking the logarithm transformation will result in a large number of undefined values, especially in the pre-Demonetization period. We adopt a commonly used alternative to the logarithm transformation, the inverse hyperbolic sine transformation, instead. Such transformation is a concave log-like transformation and allows retaining zero-valued observations.[16]

Regardless of whether we focus on the percentage or the level, we find a similar pattern: the decline in cash usage is mostly compensated by an increase in debit card usage. Usage of mobile payments also increases by a much smaller magnitude. On the contrary, high prior cash dependence leads to a small yet significant lower credit card usage following the Demonetization.

D Price level and Demonetization

We also calculate the average price level across all products sold in the supermarket chain using the following regression model:

$$y_{i,j,t} = \mu_i + \pi_j + \sum_{t \neq 0} \beta_t \mathbb{1}_t + \varepsilon_{i,j,t} \tag{5}$$

[16]For a random variable x, taking the inverse hyperbolic sine (arcsinh) transformation yields a new variable $\tilde{x}$ such that $\tilde{x} = arcsinh(x) = \ln\left(x + \sqrt{x^2+1}\right)$. In an "arcsinh-linear" specification where the dependent variable is arcsinh transformed and the explanatory variable is not, the coefficient estimate yields a similar interpretation to that of a standard log-linear specification. See Bellemare and Wichman (2020) for a formal proof.

where is $y_{i,j,t}$ is the log of the mean transaction price of product i in store j on day t, $\mathbb{1}_t$ are monthly dummies (month 0 corresponds to November 2016 when the Demonetization took place). Since November 2016 is the omitted baseline group in this log-linear specification, the exponentiated coefficient for month t corresponds to the price level of month t relative to that of November 2016. Figure OA.3 plots the exponentiated coefficients and the associated 95% confidence intervals.

Consistent with the smooth national CPI, whose year-over-year growth rate was monotonically declining from 6.068% in June 2016 to 3.167% in January 2017, the increase in the average price level across all products sold in the supermarket chain around the time when the Demonetization was announced is very modest.

References for the online appendix

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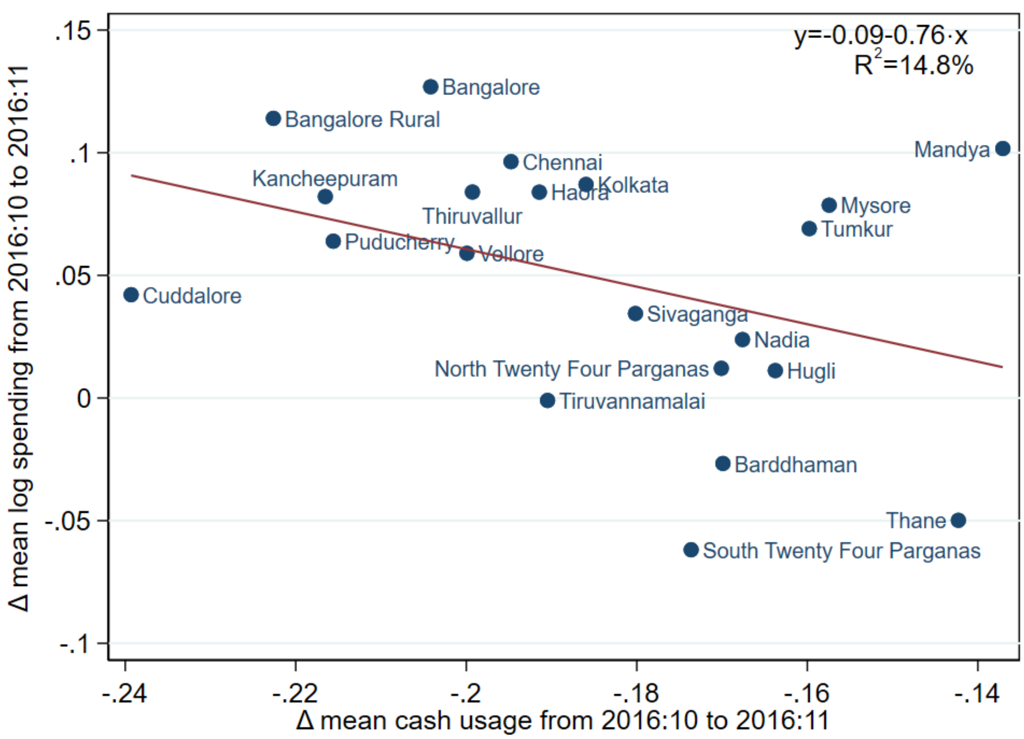
Justine S. Hastings and Jesse M. Shapiro. How Are SNAP Benefits Spent? Evidence from a Retail Panel. *American Economic Review*, 108(12):3493–3540, 2018.

Figure OA.1: **District-level cash usage and spending**

This figure shows the correlation between cash usage and spending across districts. We calculate the average cash usage and log spending for each district in each month. Panel (a) presents a scatterplot of the change in log spending from October 2016 to November 2016 and the change in cash usage during the same period. The red line gives the best-fit line. Alternatively, we first de-mean the raw level of individual-level cash usage and log spending with respect to the individual fixed effects to calculate "net" measures before taking the average for each district in each month. Panel (b) presents the scatterplot of changes in "net" measures and the best-fit line.

(a) Average cash usage and log spending for each district in each month



(b) Average net cash usage and log spending for each district in each month

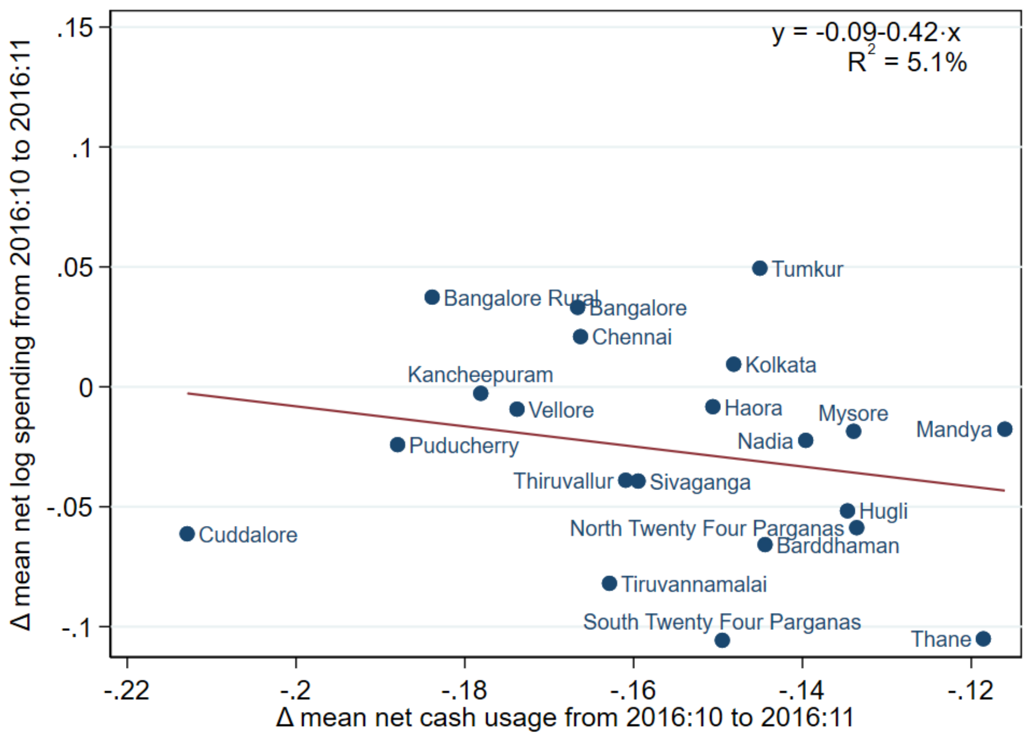
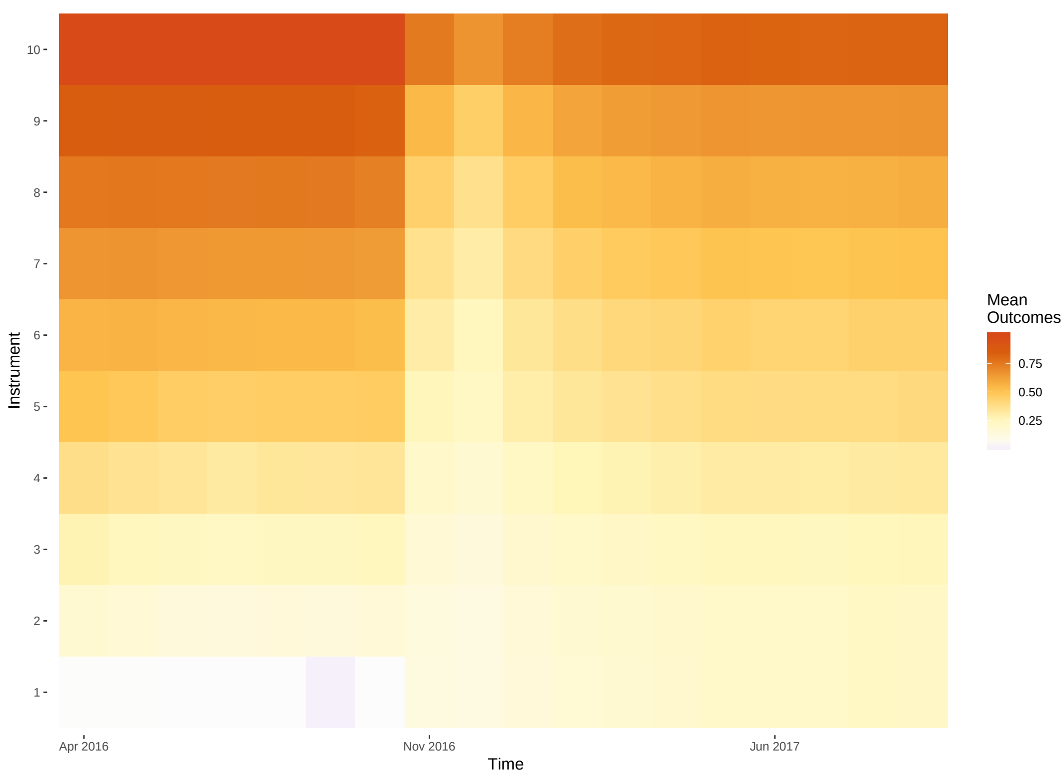


Figure OA.2: **Cash Usage and Spending Response to the Demonetization (Multi-Group Comparison)**

This figure plots the average cash usage and log spending for ten groups of consumers evenly sorted by prior cash dependence. For each consumer in the sample, the prior cash dependence is calculated as the average share of spending paid by cash from April 2016 to October 2016. Columns correspond to months and rows correspond to groups of consumers evenly sorted by prior cash dependence. Each cell's shading corresponds to a within-row average level of a key outcome variable, the share of spending paid by cash in panel (a) and the natural logarithm of spending amount in panel (b).

(a) Cash usage over time by prior cash dependence



(b) Log spending amount over time by prior cash dependence

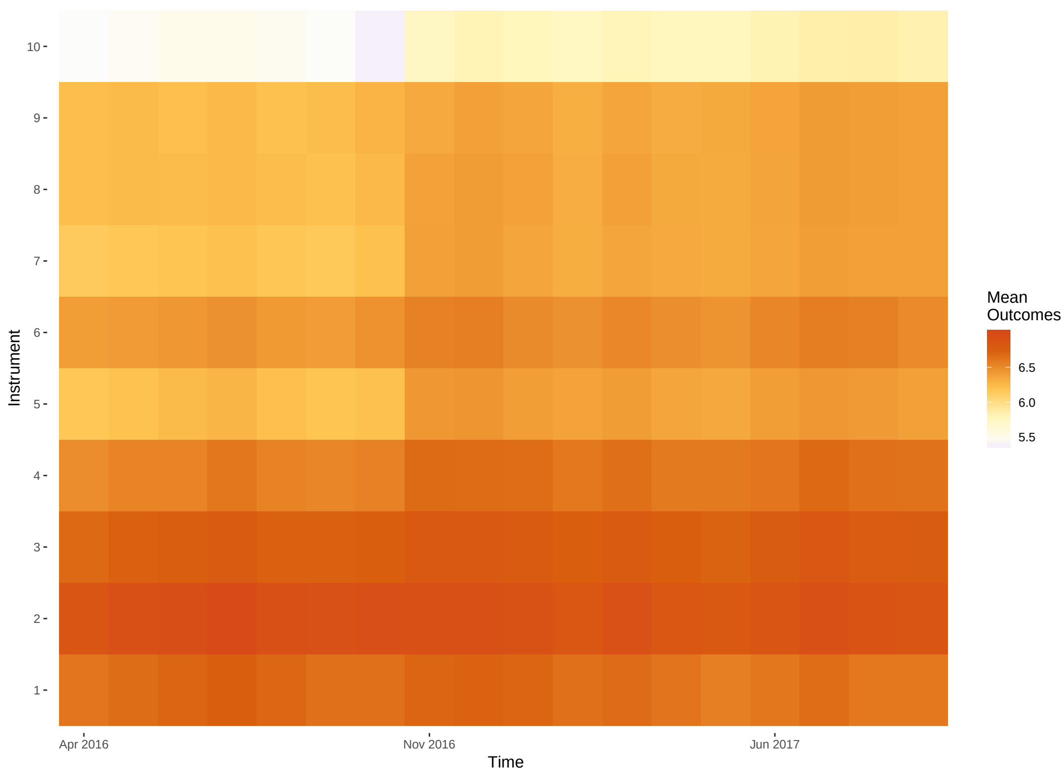


Figure OA.3: **Price level and Demonetization**

This figure shows the price level of products sold by the supermarket chain in our sample at a monthly frequency. The figure plots the exponentiated coefficients and the associated 95% confidence intervals as estimated from equation (5). Since November 2016 is the omitted baseline group in this log-linear specification, the exponentiated coefficient for month t corresponds to the price level of month t relative to that of November 2016.

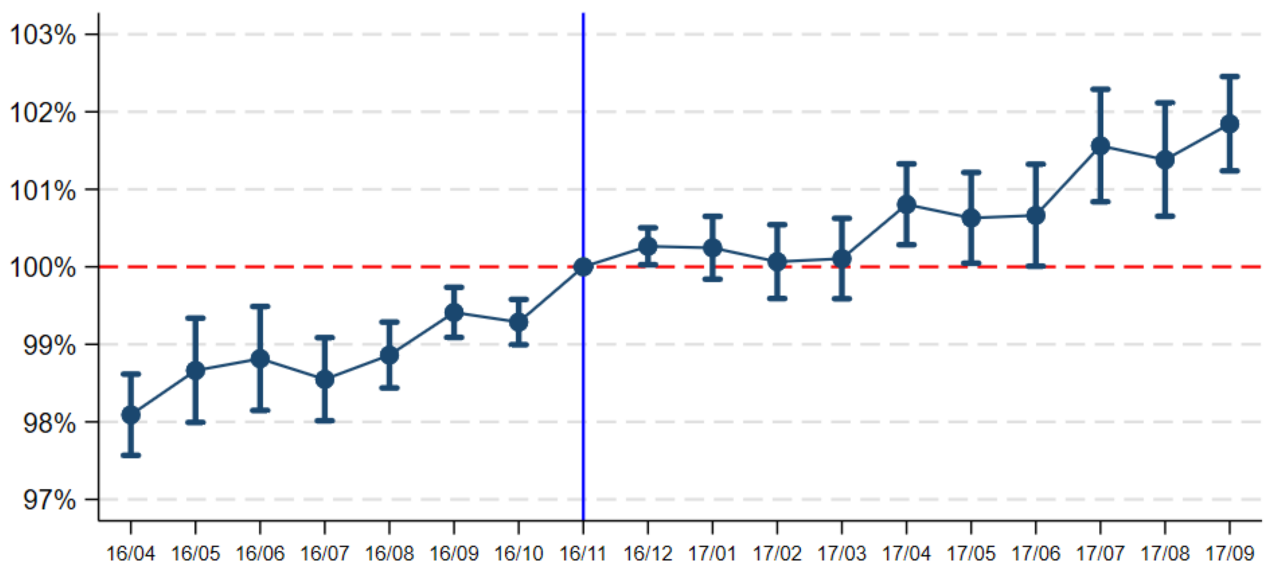


Table OA.1: **Heterogeneous forced switch to digital payments (level)**

This table estimates the effect of the forced switch to digital payments due to the Demonetization on payment methods and spending. The data are at the individual-month level from April 2016 to September 2017. For cash, debit cards, mobile payments, and credit cards, we consider the absolute level and the inverse hyperbolic sine transformed level (IHS) as the outcome variables. Post is an indicator for post-Demonetization months. Fixed effects are denoted at the bottom. Standard errors are clustered at the individual level; the corresponding t-statistics are reported in brackets. We use ***, ** and * to denote significance at 1%, 5% and 10% level (two-sided), respectively.

	Cash		Debit		Mobile		Credit	
	(1) Level	(2) IHS	(3) Level	(4) IHS	(5) Level	(6) IHS	(7) Level	(8) IHS
PriorCashDependence × Post	-180.1***	-1.397***	376.1***	2.412***	3.288*	0.00172	-38.03***	-0.163***
	[-4.85]	[-23.46]	[10.73]	[47.31]	[1.97]	[0.24]	[-3.53]	[-3.04]
Individual FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
District × Time FEs	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.425	0.519	0.447	0.579	0.358	0.345	0.403	0.443
No. of Observations	6,561,580	6,561,580	6,561,580	6,561,580	6,561,580	6,561,580	6,561,580	6,561,580