Digital Payments Induce Over-Spending: Evidence from the 2016 Demonetization in India*

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March 4, 2019

Abstract

We examine the impact of digital payments on consumer spending by exploiting a forced switch to digital payments induced by the 2016 Indian Demonetization. This policy resulted in a 86% decline in the cash that could be used for spending transactions and led cash-dependent consumers to adopt digital payments. We find that an increase of 10 percentage points in prior cash dependence increases usage of digital payments by 3.24 percentage points and monthly spending by 3%. Usage of digital payments and spending remain elevated when cash availability is replenished. The increase in spending comes from purchasing expensive products in narrowly-defined categories and using promotional offers less, and is not driven by income shock, credit supply, suppliers' pricing response, or consumers' moving to the formal market. These results highlight that digital payments can induce over-spending due to their subdued salience and shed light on the policy debate about the costs and benefits of moving to a cashless economy.

*We thank seminar participants at National University of Singapore and Singapore Management University for helpful comments. All errors are our own.

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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. Along with this transformation, digital payments[1] empowered by quickly build-up digital platforms and infrastructure in the banking system has penetrated into the life of each individual consumer and altered the way in which daily transactions are conducted.[2] It is a widespread belief that cash will die out eventually and we will have a cashless society (Arvidsson and Markendahl, 2014; Carton and Hedman, 2013).

While financial digitization brings convenience, reduces transaction costs, and improves market efficiency, replacing cash with digital payments may encourage overspending, as keeping the budget becomes less salient for consumers when cash does not change hands in transactions. Given the rapid pace at which digital payments are displacing cash, understanding this effect is important. Despite the support for this possibility from anecdotal and survey evidence, it is challenging to identify this effect in studying household spending behaviors.

The econometric challenge stems from the fact that the observed use of digital payments is an equilibrium outcome affected by the availability of digital payments as well as the awareness and willingness to use of both consumers and merchants. 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.[3] Even in a setting where merchants are willing to accept

[1]Throughout this paper, we use "digital payments" and "cashless payments" interchangeably. The definition covers debit cards, credit cards, Internet payments, and mobile payments, among others.

[2]For instance, in the United States, 24% of people make no purchases using cash during a typical week and 39% say that they do not worry about whether or not they have cash on hand according to a report by the Pew Research Center (Source: `http://www.pewinternet.org/2016/12/19/new-modes-of-payment-and-the-cashless-economy/`).

[3]Consumers' adoption of digital payments can feed back into merchants' adoption choice, and vice

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 payments on spending.

To overcome this empirical challenge, we focus on a unique episode in the adoption of digital payments. On November 8$^{\text{th}}$, 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.

These time-series dynamics alone cannot answer the question about the effects of payment methods on spending because other economic shocks occurred during the period. We study the consequences in the cross-section of individual consumers. 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, it is natural to expect that consumers who relied more on cash prior to this policy were more affected by the forced switch to digital payments. We formalize this intuition and construct an individual-level measure of forced adoption as the level of cash usage prior to the Demonetization announcement, using the detailed transaction-level data of payment methods. We validate that consumers with a higher prior cash dependence increase their usage of digital payments more following the Demonetization. We do

versa (e.g., Higgins, 2018).

so in a graphic analysis of unconditional patterns and in a difference-in-differences (DiD) panel regression setting. In the latter setting, the confounding time trends and individual demographics are controlled for by the inclusion of time fixed effects and individual fixed effects respectively. The effect is both statistically and economically significant: an increase of one percentage point in the prior cash dependence is associated with a decline of 0.324 percentage points in cash usage, and corresponding an increase of the same magnitude in digital payment usage, following the Demonetization.

Such a forced switch to digital payments is associated with an increase in spending. Using the same DiD panel specification, we find a statistically and economically significant spending response: moving from the 25th to the 75th percentile of prior cash dependence is associated with an additional spending of 96.4 rupees, or a 15% increase. In addition, we find that this cross-sectional relationship remains stable till September 2017, the end of our sample period, despite that the demonetized notes were replenished a few months after November 2016.

We also study the quantity and price of goods purchased to assess the extent to which the observed increase in spending reflects over-spending. We find strong evidence that consumers who were forced to switch to digital payments purchase expensive goods in narrowly-defined categories and use promotional offers less following the Demonetization. These patterns are consistent with the over-spending conjecture.

We address four main challenges to this identification of the effect of digital payments on consumer spending. First, one might be concerned about an income channel whereby consumers who are more exposed to the Demonetization shock experience a positive income shock and therefore increase their spending. The *ex-ante* secrecy and the slow and disorderly replenishment of notes associated with the Demonetization increased economic uncertainty greatly. It is also widely believed that such a policy posed a severe disruption to the economy. Given the elevated uncertainty and the disruptive economic effects, a positive income shock is not likely. To the extent that (relative) income re-allocation exists, consumers with higher exposure to the Demonetization shock should experience a negative, rather than positive, shock. A prior cash dependence for supermarket spending can reflect the income from black market activities to some extent. Since the black market, the target of the policy according to its stated objectives, turned out to be discouraged and confined by the policy quite successfully, there are reasons to believe that the income shock experienced by the more exposed consumers, if exists, is negative and therefore makes us underestimate the true positive impact of digital payments on spending. To empirically assess this conjecture, we proxy for black market income with the behavior of paying large receipts with cash in the pre-Demonetization period. We find a much muted spending response by consumers who engaged in black market activities according to this measure, consistent with a negative income shock.

Second, credit cards, one of the digital alternatives to cash as a payment method, 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. Credit card usage remains low throughout our sample period. Drawing on the insights from the literature on credit history and access to credit, we expect that banks 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. We find that this is the case in the cross-section of consumers: high prior cash dependence is associated with a slightly lower credit card usage following the Demonetization. We also examine existing, new, 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 be concerned that the effect of digital payments on spending is mechanically driven by the increase in product prices. This could happen if product suppliers, the manufacturers of the supermarket chain, anticipate the tendency of consumers to become less price sensitive following the adoption of digital payments and strategically increase product mark-up. We find that the average price across products in our sample increased only modestly following the Demonetization, consistent with a positive and smoothly declining national inflation rate. To investigate whether product pricing changes correlate with treatment intensity in the cross section, 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 purchases in the formal market that is observed in our data, our estimate can be biased in the upward direction. 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. To the extent that the shifting applies to existing consumers, we would expect that consumers who previously bought non-grocery goods from the supermarket have a higher spending response as they are the shifting ones. We stratify our sample to separately examine consumers falling into this category and find the opposite: high prior non-grocery spending is associated with a higher spending response.

This paper engages with several strands of literature. First, we contribute to the literature on the economic impacts of digital payments. 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). 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. Thus far, this literature has largely taken the consumption bundle as given and focus on the pecuniary costs associated with digital payments. Our paper, by contrast, emphasizes that digital payments can directly affect the consumption bundle through the salience channel.

We join a recent methodological improvement that analyzes large-scale new datasets in quasi-experimental settings to more credibly identify the causes and consequences of digital payments adoption. Higgins (2018) studies the interaction between merchants' adoption and consumers' adoption in the context of a government roll-out of debit cards in Mexico. Our paper builds on the findings by Agarwal et al. (2018) and Crouzet et al. (2019) that the drying-up of cash due to Demonetization leads to a substantial and persistent rise in the adoption of digital payments.

We also relate to D'Acunto et al. (2018), who study the effects of an unexpected announcement of a future increase in value-added tax, a form of unconventional fiscal policy, on households' inflation expectations and willingness to purchase. Both government policies studied in D'Acunto et al. (2018) and in our paper affect households' consumption without changing their income. Our paper differs in two 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, as opposed to survey data, to characterize households' spending response.

Our paper also sheds light on the policy debate about the costs and benefits of moving to a cashless economy. Cash poses substantial costs to the financial system and the economy as a whole: not only is it costly to manufacture, safeguard, collect, and circulate, it also puts a floor on the nominal interest rate and facilitates illegal activity and tax evasion as Rogoff (2017) points out. Cash is more heavily used in India and many emerging countries alike compared to developed economies. 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 results highlight the salience features of different payment methods and suggest that a move from cash payments towards digital payments could have an unintended consequence of encouraging people to over-spend.

The paper proceeds as follows: Section 2 provides an overview of the empirical setting, describes the data, and lays out the empirical approach; Section 3 presents our main results; Section 4 presents our analysis for addressing alternative explanations; Section 5 provides a brief discussion for how to interpret the results as well as the welfare implications; Section 6 concludes.

2 Empirical Setting

A 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 they would 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.[4]

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. Prior to 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: the value of new 500 and 2000 notes, as a share of total pre-announcement currency-in-circulation, started at less than 10% right after November 8th and reached only 40% in February 2017 and 60% in June 2017 based on currency chest data (Chodorow-Reich et al., 2018).

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

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

payment systems for ushering in a less-cash society" for the country's payment system in 2012.[5] Such a vision has been cultivated by policies and regulations such as the rationalization of the Merchant Discount Rates and the issuance of RuPay cards under the Prime Minister Jan Dhan Yojana scheme.[6] These policies, however, had not changed the dominant role of cash in payment methods as of 2015. Although the number of debit card 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.[7] The large and sudden Demonetization event in November 2016 represents a forced switch away from using cash for transactions.

B Data and Summary Statistics

We use customer receipt-level transaction data from a large supermarket chain in India. This store, the fourth largest supermarket chain and the third largest private-sector business group in India, has annual revenue of more than 35 billion rupees (525 million dollars) and operates 530 stores across India. The merchant's loyalty program makes tracking consumers possible. The data we obtained covers the universe of all transactions from 171 stores out of the 530 stores, tagged with anonymized consumer identifier. The sample period is April 2016 to September 2017. The data contains information on store information, receipt amount, payment method, and details of items purchased.

Table 1 reports the summary statistics. The average monthly purchase is 1018.64

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

[6] Source: RBI's Concept Paper on Card Acceptance Infrastructure published on March 8th 2016, available at `https://www.rbi.org.in/Scripts/PublicationReportDetails.aspx?UrlPage=&ID=840`.

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

rupees (15.28 dollars). As a comparison, monthly gross disposable income per capita is 6973 rupees (104.6 dollars) in 2016 according to the Central Statistics Office. The average monthly purchase we observed in our data accounts for 14.6% of the monthly gross income.

Figure 1, which plots the shares of different payment methods 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 (credit cards and mobile payments) remains low. The composition of payment methods in the pre-Demonetization era in our sample is broadly in line with earlier aggregate statistics as well as more recent composition data reported by other studies that use transaction data. For example, Agarwal et al. (2018) report that cash on delivery accounted for 57% of all online shopping transactions as of 2015, followed by debit cards (15%), credit cards (11%), online banking (9%), and mobile payments (8%). Given that shoppers in physical stores such as the ones we study here are typically less technology-savvy than online shoppers, one would expect that the adoption of digital payments was lower among shoppers in physical stores, which is what we report here.

C Mechanisms

Why should consumer spending depend on the payment method? In this section we discuss some possible mechanisms pertaining to the salience of payment methods. Collectively, they suggest that cash is a more salient payment method than digital alternatives. When consumers move from cash towards digital payments, they can over-spend due to the subdued salience of paying for purchases.

While the standard economic theory assumes that consumer valuations of products and services are independent of how money is represented, distinctive features of payment instruments begin to play a role through affecting salience when we consider richer and more realistic nuances influencing consumer behaviors.

The first mechanism plays the role of *a decision point*. A payment mechanism that is effortful and involves some transaction costs/constraints can serve as a decision point for consumers to evaluate their expenses. However, plastic mechanisms such as debit cards and credit cards remove those decision points and hence make spending easier.

The second mechanism involves *memorability of past expenses* and hence the accuracy of the mental accounting: People who use debit or credit cards tend to underestimate their past expenses in a given month, overestimate their available funds, and hence spend more.

The third mechanism is the notion of *"pain of paying" or payment transparency*. 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, plastic mechanisms are simpler and shorter as no money actually exchanges hands. This is analyzed by (Prelec and Loewenstein, 1998; Zellermayer, 1996; Soman, 2003; Raghubir and Srivastava, 2008).

The pain of paying is also related to *transaction decoupling* (Gourville and Soman, 1998; Soman and Gourville, 2001; Thaler, 1999). In the case of advance purchases using credit cards, consumers gradually adapt to the pain of the payment over time, such that when the time to pay finally arrives, the payment is no longer aversive and the good appears to be a free good. The prospect theory (Kahneman and Tversky, 1979) also predicts that the payment will not sting as much in the bundled credit card condition, because it is integrated with other losses.

Last but not the least, a payment method can *feedback to consumer behaviors* (Hogarth et al., 1991). The provision of feedback allows consumers to learn and hence update their behavior. In the case of credit cards, feedback arrives in the form of periodic statements that are neither timely nor consistent with household budgeting cycles.

Regardless of the exact mechanisms, cash is a more salient payment method than digital alternatives. Among different alternatives, there is a varying degree of salience as summarized in Table 2.

D Empirical Approach

We are interested in estimating the elasticity of spending to the usage of digital payments. The key prediction of the various mechanisms summarized above is that digital payments encourage over-spending through their 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 high-income individuals have better access to digital payments and spend more relative to low-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. This is especially true when mobile payments and faster tap-and-go technology are not available. This mechanical relationship is borne by the data in our sample: The mean (median) receipt amount paid with cash is 204.28 (88) rupees while the mean (median) receipt amount paid with digital payments is 620.79 (292.5) rupees.

Both the omitted variable and the reverse causality are 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. The following simple two-group comparison showcases this standard "reflection" problem: When we compare full cash users and mixed cash users, classified each month, we see that full cash users consistently spend less than mixed cash users throughout our sample period (Figure 2).

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. When these consumers then make their purchase decisions and pay for their purchase using their assigned payment methods, any variation in their spending amount would be orthogonal to all consumer characteristics and therefore reflect the impact of payment methods. We adopt a quasi-random approach, taking advantage of the cross-sectional variation in the 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 difference-in-differences (DiD) framework.

The basic idea behind the identification strategy can be illustrated using a simple two-group comparison. Figure 3 shows means of cash usage and spending for different prior cash dependence. Consumers are separated into "full cash users" and "mixed cash users" based on their payment behaviors from April 2016 to October

2016. Figure 3a shows that while both full cash users and mixed cash users decreased their usage of cash following the policy, full cash users experienced a larger decline. Figure 3b shows that full cash users increased their spending significantly following the Demonetization, whereas mixed users had flat spending before and after the Demonetization.

The identifying assumption central to a causal interpretation of our DiD estimates is that individuals with varying prior cash dependence share parallel trends. Figure 3 and the additional tests that take into account the continuous nature of the treatment presented in the next section show that their pre-treatment trends are indeed indistinguishable. The question, as in any DiD set-up, is whether post-treatment trends would have continued to be parallel had it not been for the Demonetization. To mitigate the concern that they may not have been, we control for all unobserved heterogeneity in the cross section with individual fixed effects, and for shocks to the economic uncertainty and the price level with time fixed effects. As a result, our estimation compares changes in spending within individuals instead of comparing changes in spending across individuals.

3 Evidence for Over-Spending Induced by Digital Payments

We begin with a simple graphical analysis that 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 they increased spending significantly. Such a spending response persists despite the gradual replenishment of the demonetized notes.

Figure 4 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), the absolute level of spending in panel (b), and the natural logarithm of spending amount in panel (c).

These heatmaps yield third conclusions. First, cash usage was stable for every group prior to the policy. 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 shock. More importantly, every sequence of consecutive months in the pre-period provides a placebo test that fails to reject 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 smooth increasing digital payment usage, in November 2016 shows the switch to digital payments is monotone in pre-determined exposure and not driven by a few outlier consumers or consumer groups.

Third, the gradient does not appear to reverse back to the pre-Demonetization levels in the ten months following the Demonetization despite the replenishment of the demonetized notes. The data do not indicate a sharp reversal of the spending response.

Next, we present statistical results in a difference-in-differences (DiD) panel regression setting. This approach allows us to use all of the variables in the data as well as to include fixed effects to control for unobserved characteristics that are invariant in certain dimensions that one might think as confounding factors. The baseline specification is as follows:

$$y_{i,t} = \alpha + \beta \left(PriorCashDependence_i \times Post_t \right) + \mu_i + \pi_t + \varepsilon_{i,t} \tag{1}$$

$y_{i,t}$ is a measure of spending behavior (spending amount, payment pattern) of consumer i at month t. The key variable of interest is the interaction between $PriorCashDependence_i$, an consumer-level measure of prior cash dependence, and $Post_t$, an indicator for post-Demonetization months. Its coefficient β measures the forced switch to digital payments. Consumer fixed effects μ_i remove unobserved cross-sectional heterogeneity and time fixed effects π_t remove unobserved time-varying heterogeneity. This specification augments a standard difference-in-differences specification by taking a flexible and agnostic approach to account for treatment intensity (subsumed by individual fixed effects) and the post dummy (subsumed by time fixed effects). The regression thus compares changes of payment and spending behaviors within individuals instead of comparing changes across individuals. Standard errors are robust and clustered at the consumer level.

The results are reported in Table 3. Column 1 provides direct evidence of the forced switch to digital payments induced by the Demonetization: an increase of ten percentage points in the prior cash dependence is associated with a decline of 3.24 percentage points in cash usage following the Demonetization. Note that according to our definition of digital payments, a decline in cash usage reflects an increase in digital payments of an equal magnitude. Column 2 indicates that an increase of ten percentage points in the prior cash dependence is associated with an increase of 19.27

rupees in the level of monthly spending. An analysis using the inter-quartile range of prior cash dependence can demonstrate the economic significance of this estimate: the 25$^{\text{th}}$ and 75$^{\text{th}}$ percentiles of prior cash dependence are 50% and 100%. Therefore a consumer at the 75$^{\text{th}}$ percentile increases spending by 96.4 (19.27×5) rupees relative to a consumer at the 25$^{\text{th}}$ percentile. This additional spending corresponds to close to 10% of the unconditional mean of monthly spending in our sample. Column 3 reports the result for log spending as the outcome variable. According to the estimate from this specification, an increase of ten percentage points in the prior cash dependence is associated with a 3% increase in monthly spending. Therefore, a consumer at the 75$^{\text{th}}$ percentile increases spending by 15% relative to a consumer at the 25$^{\text{th}}$ percentile.

We also decompose total spending by payment methods. Table 4 reports the results for the fraction of total monthly spending paid by debit cards, mobile payments, and credit cards as the outcome variable; Table 5 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 prior to 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.[8]

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. Adoption of Mobile payments also has a statistically significant increase,

[8]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 (2018) for a formal proof.

albeit with a minuscule economic magnitude. On the contrary, high prior cash dependence actually leads to a small yet significant lower credit card usage following the Demonetization.

In Table 6, we report the results estimated from the sample excluding full cash users prior to the Demonetization. Compared with the results obtained from the full sample (Tables 3 and 4), we can see that the effects on the usage of each payment method and on the absolute level of spending are quantitatively similar, but the effect on log spending is smaller.

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 that she no longer needs to carry and count bills and coins. She is unlikely to go back to the traditional way of paying by cash. The sustained lighter shading for every group in the post-Demonetization period compared to the prior period in Figure 4 provides support for this possibility.

To empirically investigate this, we augment Equation (1) to examine the dynamic effects by replacing the post-Demonetization indicator variable with indicator variables for each calendar month.

$$y_{i,t} = \alpha + \sum_{t} \beta_t \left(PriorCashDependence_i \times \mathbb{1}_t \right) + \mu_i + \pi_t + \varepsilon_{i,t}$$

We trace out the betas associated with the interaction between prior cash dependence and the monthly indicator variables in Figure 5. This analysis also provides another test of the parallel trends assumption underlying our research design. The cash usage and the spending response remain stable throughout our sample period. Table 7 which report the results estimated from the sample excluding the first three months following the Demonetization announcement (November 2016, December 2016, and January 2017) confirms that the spending response is unchanged when cash made a comeback to the economy.

So far we have shown that the Demonetization induces consumers who on average relied heavily on cash for paying supermarket receipts to adopt digital alternatives and increase spending. To what extent can this increase in spending be viewed as over-spending? To provide perspectives on this, we exploit the richness of our data and analyze the types of products consumers buy as well as the prices they pay.

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 the purpose of this analysis, we use the two most granular categorizations. Examples of the second most granular categories include "Cereals - Pulses and Flours," "Fruits," and "Cooking Appliances," and "Infant Underwear & Night Wear". Each of these categories can be further broken down into a few of the 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 run the following regression for consumer i's spending in category c in month t:

$$y_{i,c,t} = \alpha + \beta\,(PriorCashDependence_i \times Post_t) + \mu_i + \pi_{c,t} + \varepsilon_{i,t} \tag{2}$$

We examine four outcome variables for this analysis: the rupee amount spent on the category (Amount), the quantity of goods purchased (Quantity), the unit price of goods purchased (Unit Price), and the use of promotional offers measured from the listing price and the actual price paid (Use Offer). Similar to Equation (1), the key variable of interest is the interaction term between $PriorCashDependence_i$ and $Post_t$. Its coefficient β measures the impact of Demonetization. In this specification, we are comparing the within-individual change by including consumer fixed effects μ_i. The category-time fixed effects $\pi_{c,t}$ subsume factors such as the seasonality in product demand and supply and the supplier's pricing responses.

The results are reported in Table 8. Columns of odd-numbers report the results following Equation (2). In columns of even-numbers, we replace the consumer fixed effects with a more granular set of fixed effects, the consumer-category fixed effects $\mu_{i,c}$, to take into account the potential difference in spending profiles across consumers.

Using both specifications, we find a positive coefficient for all four outcome variables examined. The effect is strongest for Unit Price and Use Offer: The treated consumers buy more expensive products and make advantage of promotional offers less following the Demonetization. These results suggest that the observed increase in spending likely reflects over-spending.

4 Addressing Identification Challenges

To test for the effect of digital payments on spending, ideally one would randomly assign identical consumers to cash and digital payment methods that are both accepted in the merchant. When these consumers then make their purchase decisions and pay for their purchase using their assigned payment methods, any variation in their spending amount would be orthogonal to all consumer characteristics and therefore reflect the impact of payment methods. In this section, we address four important challenges to our identification that arise from deviations of our empirical setting from this ideal experiment: income shock, credit supply, suppliers' pricing response, and consumers' moving to the formal market.

A Identifying Concern 1: Income Shock

One might be concerned about an income shock channel whereby consumers who are more exposed to the Demonetization shock experience a positive shock and therefore increase their spending. The *ex-ante* secrecy and the slow and disorderly replenishment of notes associated with the Demonetization increased economic uncertainty greatly. 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."[9] Chodorow-Reich et al. (2018) find that the Demonetization lowered the growth rate of economic activity by at least 2 percentage points in the fourth quarter of 2016. Thus, a positive income shock is unlikely to occur.

Although the elevated uncertainty and the evidence on aggregate economic conditions do not entirely preclude a re-allocation of (relative) income among individuals of varying exposure to the Demonetization shock, it does make the conjecture of income growth less plausible.

To the extent that income re-allocation exists, consumers with a higher treatment

[9]Source:http://theconversation.com/the-shock-of-indian-demonetisation-a-failed-attempt-to-formalise-the-economy-93328.

intensity should experience a negative, rather than positive, shock. A prior cash dependence for supermarket spending can reflect the income from black market activities to some extent. Black market activities, the target of the policy according to its stated objectives, turned out to be discouraged and confined by the policy quite successfully: 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. There are reasons to believe that the income shock experienced by the more exposed consumers, 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. We do not directly observe households' source of income, so we cannot exactly identify who draw income from black market activities. We proxy for black market income with the behavior of paying large receipts with cash in the pre-Demonetization period. This proxy is motivated by the cash-based nature of black markets. 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. 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 2.D.

In the empirical implementation, we define large receipts as receipts with amount at least as large as the 90th percentile (467 rupees[10]) in the size distribution observed

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

from all receipts paid by cash from April 2016 to October 2016. Table 9 reports the estimation results. We find a much muted response by households who were likely to engage in black market activities, consistent with the negative income shock.

B Identifying Concern 2: Credit Supply

Credit cards, one of the digital alternatives to cash as a payment method, 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. Due to the inflow of deposits to the banking sector following the Demonetization, such a conjecture of increased credit supply is plausible in theory.

First, we note that credit card usage remains low throughout our sample period. In Figure 1, the dotted line which includes the fraction of credit cards and mobile payments only increases slightly in November 2016 from the previous month. The decline in cash usage is mostly compensated by the uptick in debit card usage. This aggregate pattern implies that the increase in digital payments takes the form of debit card on average. Given its low usage rate, it is unlikely that credit supply is driving our results.

Can banks increase credit supply to consumers who relied primarily on cash in a targeted way 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 that banks 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 Tables 4 and 5 that high prior cash dependence actually 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; 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 results are reported in Table 10.

As can be seen in Column 2, the spending response associated with prior cash dependence has a smaller magnitude in the sample of existing users than in the full sample. The sample of existing users is 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 surprisingly 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 increases, it should increase 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. The result is reported in 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 result based on the subsample of new users, as shown in Column 5, also provides evidence for increased credit supply. The post-Demonetization spending by new users is 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.

Column 4 reports the result in the subsample of credit card non-users, defined as consumers who never used any credit card in the sample period. Two findings stand out as worth mentioning here: First, the comparison of sample sizes shows that the majority of consumers in our sample are non-users — 75% in terms of individual-monthly observations. Second, the spending response is virtually unchanged in this subsample.

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

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 the tendency of 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 was monotonically declining from 6.068% in June 2016 to 3.167% in January 2017 (CEIC Data). We also calculate the average price level across all products sold in the supermarket chain (Figure 6). Consistent with the national CPI, the increase around the time when the Demonetization was announced is very modest. The time fixed effects we include in our regression specifications also directly control for the general price level that varies in the time-series dimension. 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:

$$y_{i,j,t} = \alpha + \sum_{t \neq 0} \beta_t \mathbb{1}_t + \sum_{t \neq 0} \gamma_t \left(\mathbb{1}_t \times \mathbb{1} \left(HighExposure_i \right) \right) + \mu_i + \pi_j + \varepsilon_{i,j,t} \tag{3}$$

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 dummies with month 0 corresponding to November 2016 when the Demonetization took place and being the omitted baseline group. 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. The results are plotted in

Figure 7. We find no evidence that high-exposure products experienced a larger price increase than low-exposure products.

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 purchase to formal markets such as the supermarket we study 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.

First, new consumers that arrived after the Demonetization are excluded from our analysis and thus do not contribute to our identification. Second, if this possibility is driving our results, consumers who mainly bought non-grocery goods in the supermarket chain are likely to be those consumers that are shifting their grocery purchase and therefore should exhibit a higher spending response following the Demonetization.

To test this, we stratify our sample to examine consumers falling into this category separately. As the majority of goods sold in the supermarket chain are grocery products, the distribution of pre-Demonetization fraction of grocery spending in total spending is naturally skewed towards 100%. We use 95% as the cutoff for creating the two subsamples to balance the tension between meaningful variation and comparable sample sizes. We examine cash usage, total spending, grocery spending, and non-grocery spending for each group of consumers. For total spending as well as the break-down of spending into grocery and non-grocery parts, we use the inverse hyperbolic sine transformation, same as some of the previous specifications, to accommodate the large number of zero non-grocery spending observations. The results are reported in Table 11. We can see that low prior grocery spending is associated with a higher spending response, opposite of what the shifting purchase possibility suggests.

5 Discussions

Digital payments have gained widespread popularity in recent decades. The fast pace at which they are displacing cash leads to the conjecture that we will eventually move towards a cashless economy. 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 be the victim of fraud. From the perspective of financial development, digital payments can also facilitate better financial intermediation. Due to these benefits, many central banks and governments, in both developed and emerging economies, have been promoting the usage of digital payment instruments.

Digital payments can, however, induce over-spending 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.

The causal evidence for over-spending induced by digital payments we provide in this paper contributes to the policy debate about the costs and benefits of moving towards a cashless economy. The direct operation costs of cash are substantial for the financial system and 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. These direct costs are particularly important to a primarily cash-based economy such as India. It is estimated that the Reserve Bank and commercial banks in India spent about 210 billion rupees (3.15 billion dollars) in currency operation costs annually (Mazzotta et al., 2014). Moreover, there are indirect, societal costs of cash such as curbing the effectiveness monetary policy by putting a floor on the nominal interest rate and facilitating illegal activity and tax evasion, as articulated by Rogoff (2017).

Our paper focuses on a different, less studied perspective on this issue. We highlight the salience features of different payment methods and suggest that a move from cash towards digital payments could have an unintended consequence of encouraging people to over-spend, which in turn can undermine sound personal financial planning.

6 Conclusion

We study the unique episode in the adoption of digital payments, 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 cross-sectional empirical approach, we find that consumers who are forced to adopt digital payments increase their spending.

In interpreting the causality implications, we argue that income shock, 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 purchase more expensive goods and take advantage of promotional offers less, our analysis points to 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.

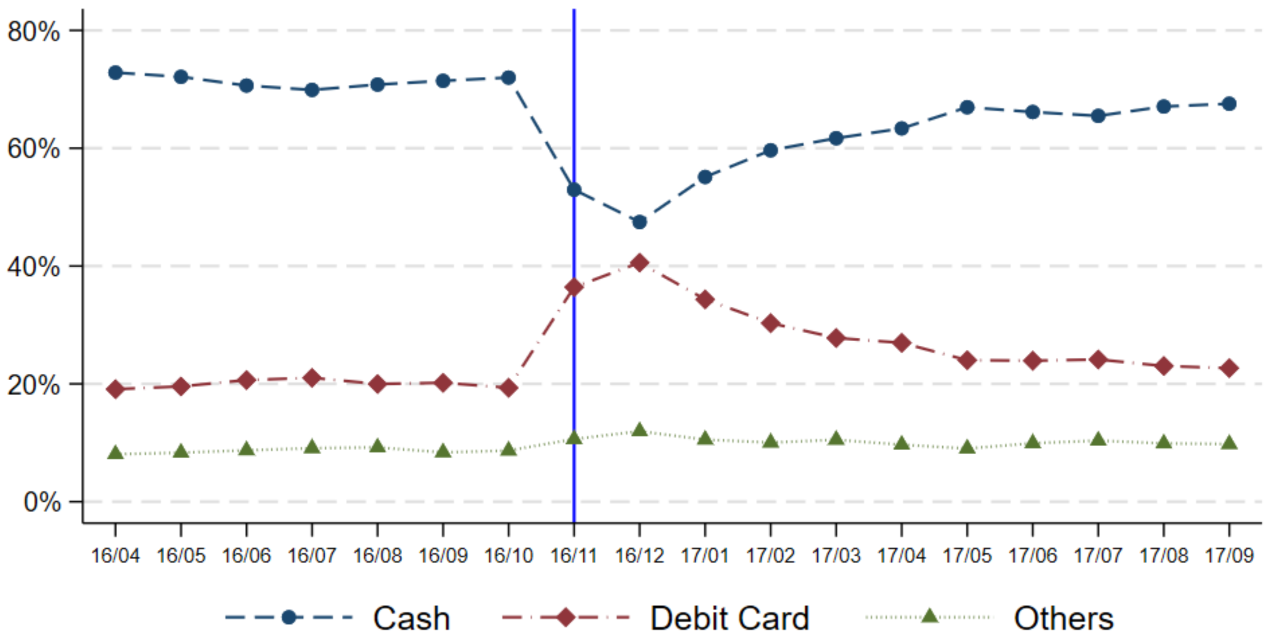


Figure 2: **Endogenous Determination of Cash Usage and Spending**

This figures plots the within-group average of log spending amount for two groups of individuals, those who use only cash and those who use cash and other payment methods in a given month.

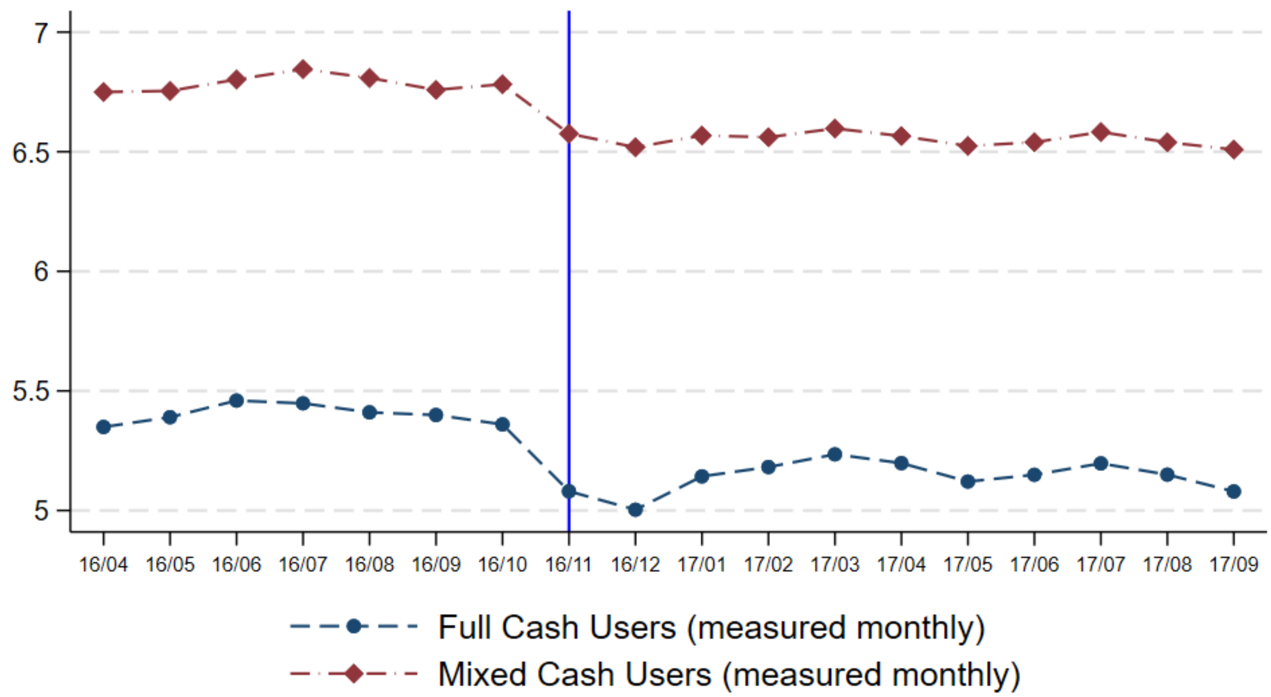
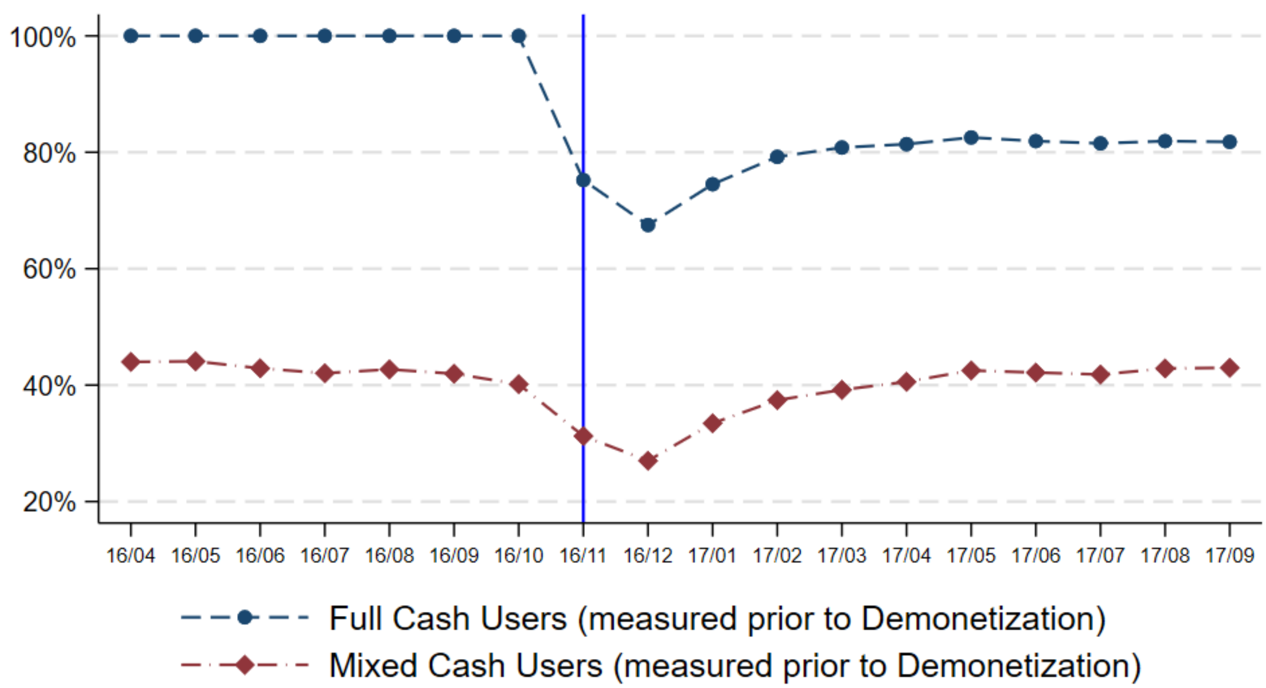


Figure 3: **Cash Usage and Spending Response to Demonetization (2-group illustration)**

This figure plots the average cash usage and log spending for "full cash users" and "mixed users" classified based on payment methods from April 2016 to October 2016.

(a) Cash usage over time



(b) Log spending amount over time

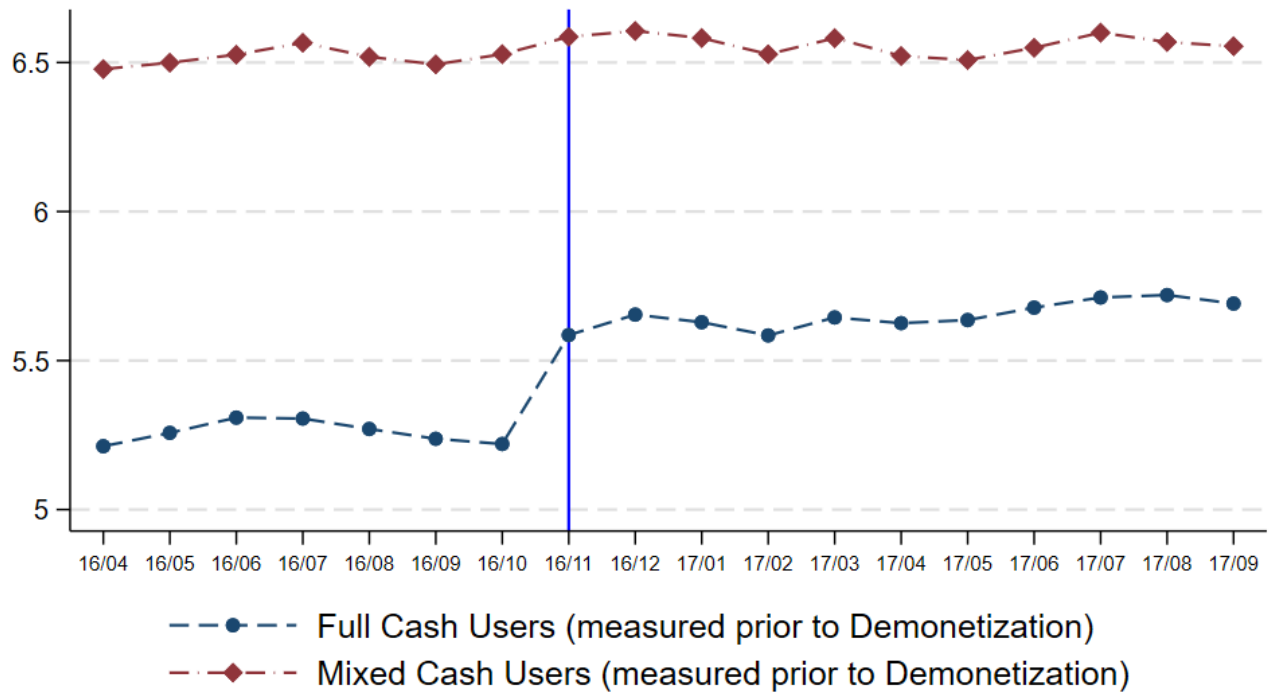
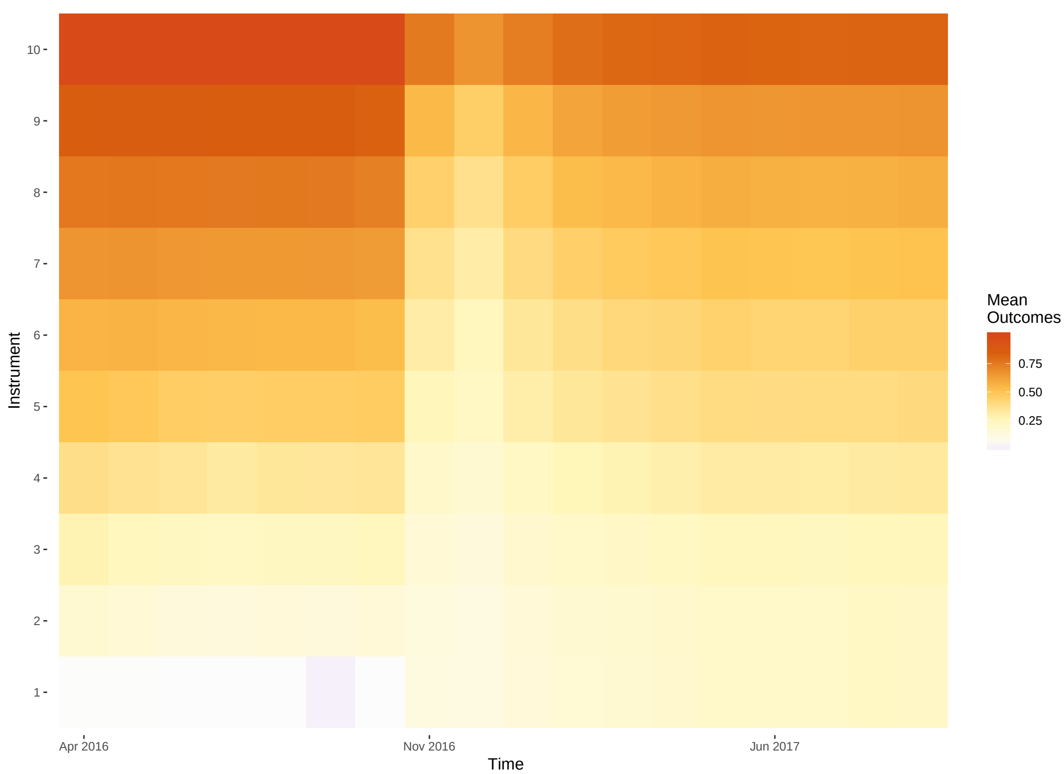


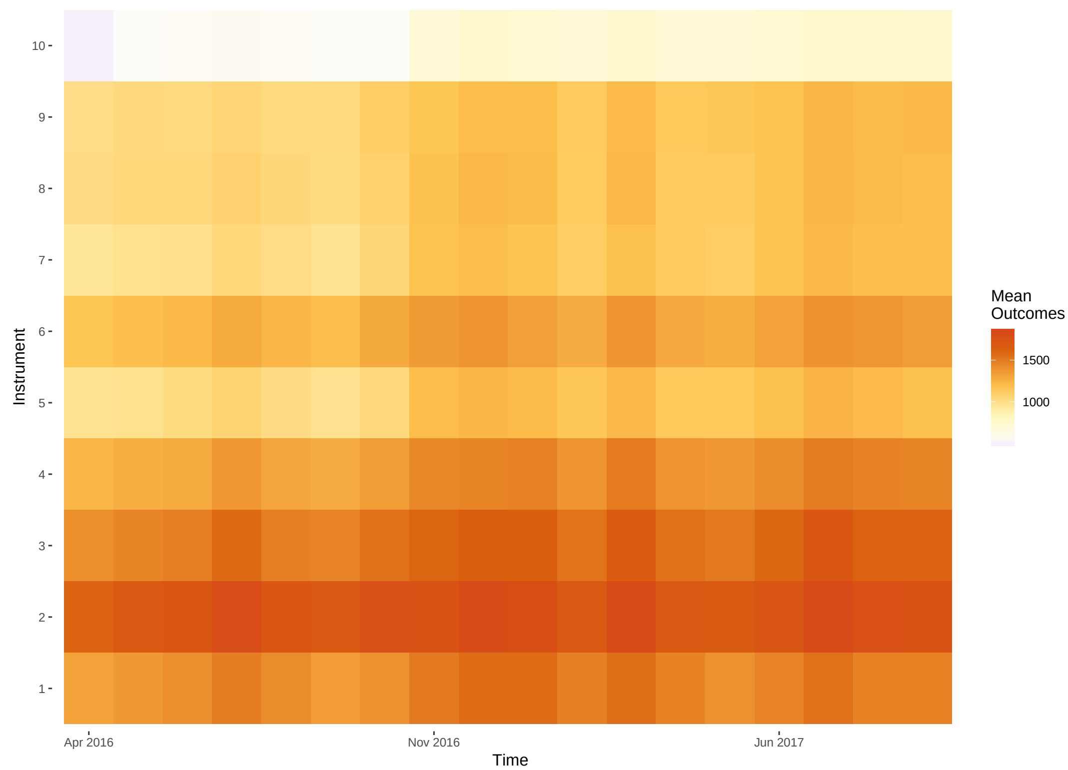
Figure 4: **Cash Usage and Spending Response to the Demonetization**

These figures plot the monthly and dynamic effects of the Demonetization on payment and spending at the individual level. Each panel plots a difference-in-differences calendar time heatmap of a key outcome variable for consumers divided into 10 evenly-spaced groups of pre-Demonetization cash usage. 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), the absolute level of spending in panel (b), and the natural logarithm of spending amount in panel (c).

(a) Cash usage over time by pre-Demonetization cash usage



(b) Spending amount over time by pre-Demonetization cash usage



(c) Log spending amount over time by pre-Demonetization cash usage

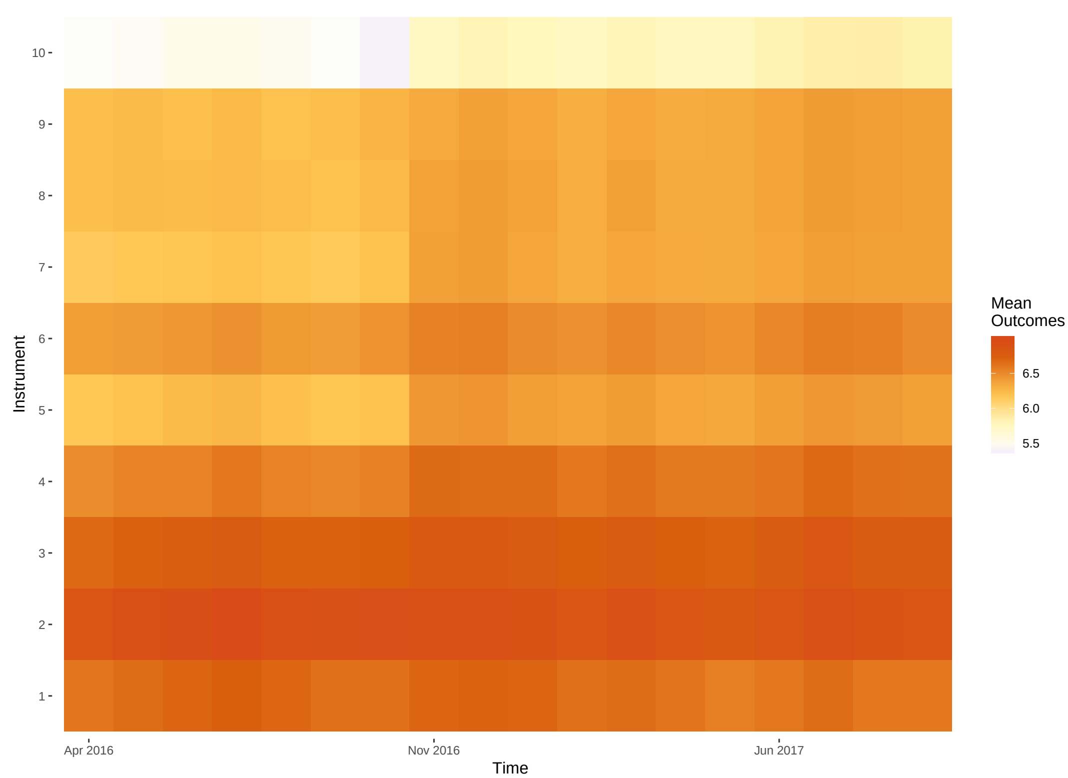


Figure 5: **Dynamic effects of digital payments on spending**

This figure shows the dynamic effect of digital payments.

$$y_{i,t} = \alpha + \sum_t \beta_t \times PriorCashDependence_i \times \mathbb{1}_t + \mu_i + \pi_t + \varepsilon_{i,t}$$

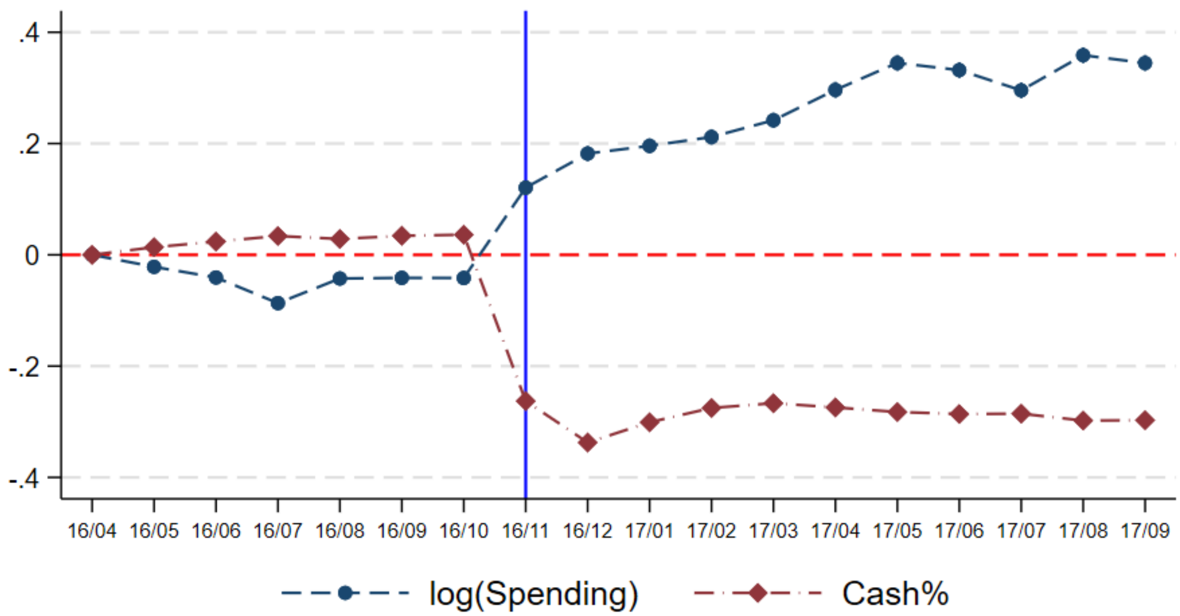


Figure 6: **Price level and Demonetization**

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 coefficient and the associated 95% confidence interval of the following regression:

$$y_{i,j,t} = \alpha + \sum_{t \neq 0} \beta_t \mathbb{1}_t + \mu_i + \pi_j + \varepsilon_{i,j,t} \tag{4}$$

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.

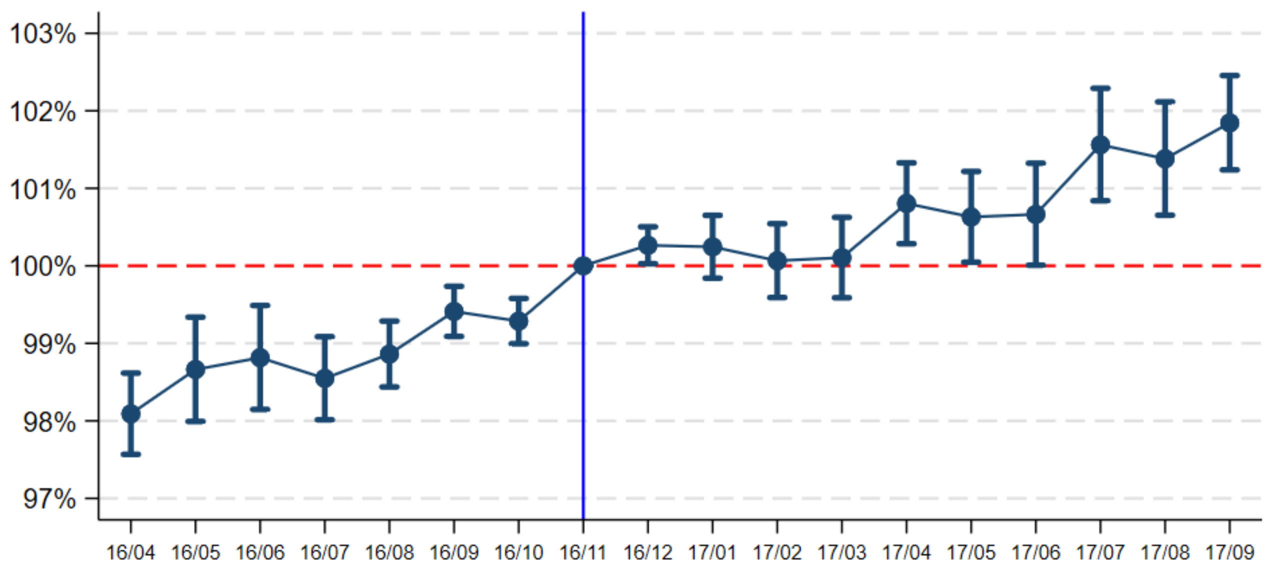


Figure 7: **Price level by pre-Demonetization exposure to cash-dependent consumers**

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 coefficient and the associated 95% confidence interval of the following regression:

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

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 and is the omitted baseline group). 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 dummy 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.

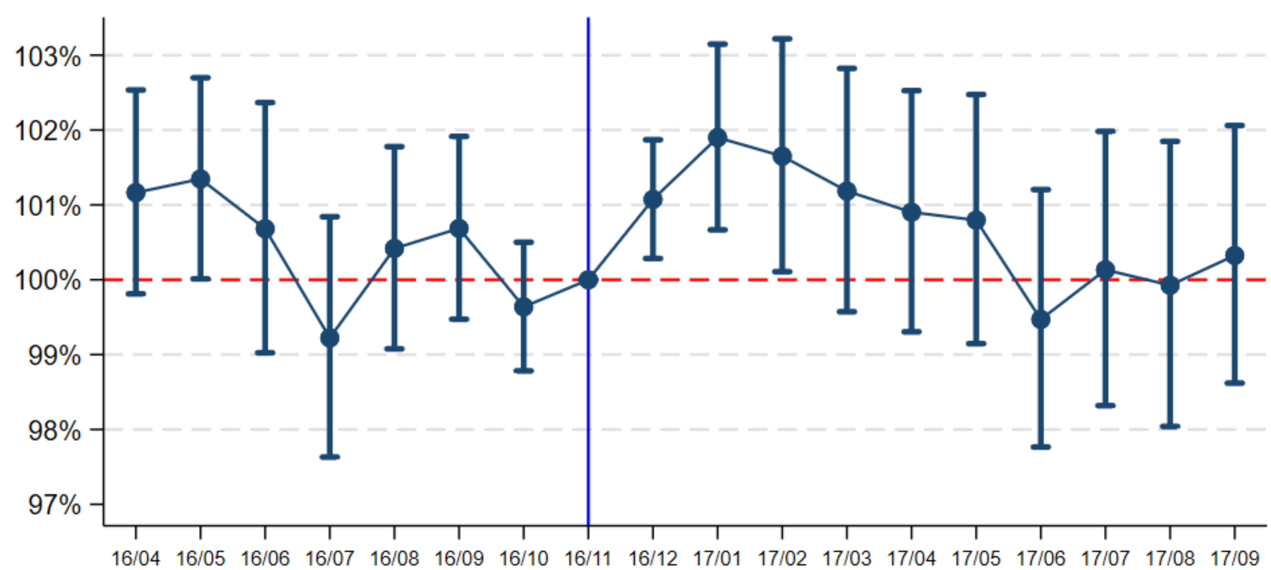


Table 1: **Summary statistics**

Summary stats

Variables	Mean	Standard Deviation
Purchase Amount per Transaction	373.92	969.95
Log(Purchase Amount per Transaction)	4.96	1.65
Dummy for Non-cash Payment	0.34	0.47
Purchase Amount per Month	1018.64	24219.97
Log(Purchase Amount per Month)	6.02	1.44
% of Non-Cash Spending per Month	0.36	0.45
% of Cash Spending per Month prior to the Shock	0.7	0.38

Table 2: **Summary of Salience of Different Payment Methods**

	Mode of Payment			
Mechanism	Cash	Debit Cards	Mobile Payments	Credit Cards
Decision Point at Purchase	High	Low	Very Low	Low
Memorability	High	Low	Low	Low
Pain of Payment	High	Low	Low	Low
Degree of Coupling	High	Medium	Medium or Low	Low
Quality of Feedback	High	Medium	Low	Low
Salience	High	Medium	Low	Low

Source: Soman et al. (2011).

Table 3: **Forced switch to digital payments and its effect on spending**

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. 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 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.

	(1) Cash usage	(2) Spending	(3) Log(spending)
PriorCashDependence $\times$ Post	-0.313***	192.661***	0.300***
	[-429.49]	[22.07]	[123.90]
Consumer Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
R^2	0.626	0.436	0.593
No. of Observations	7,644,270	7,644,270	7,644,270

Table 4: **Heterogeneous forced switch to digital payments (percentage)**

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. Cash usage, Debit usage, Mobile usage, and Credit usage are the fraction of spending paid by cash, debit cards, mobile payments, and credit cards by a given consumer in a given month, respectively. 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.

	(1) Cash usage	(2) Debit usage	(3) Mobile usage	(4) Credit usage
PriorCashDependence × Post	-0.313***	0.268***	0.001***	-0.024***
	[-429.49]	[311.06]	[6.71]	[-55.26]
Consumer Fixed Effects	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes
R^2	0.626	0.568	0.359	0.368
No. of Observations	7,644,270	7,644,270	7,644,270	7,644,270

Table 5: **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	-181.0***	-1.244***	305.0***	2.205***	3.183***	0.000142	-47.77***	-0.213***
	[-57.32]	[-210.92]	[96.09]	[318.08]	[6.47]	[0.08]	[-37.94]	[-50.63]
Consumer Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.426	0.522	0.418	0.580	0.360	0.350	0.401	0.407
No. of Observations	7,644,270	7,644,270	7,644,270	7,644,270	7,644,270	7,644,270	7,644,270	7,644,270

Table 6: **Digital payments and spending in the sample excluding full cash users**

This table estimates the effect of the forced switch to digital payments due to the Demonetization on payment methods and spending in the sample excluding full cash users prior to the Demonetization. The data are at the individual-month level from April 2016 to September 2017. Cash usage, Debit usage, Mobile usage, Credit usage are the fraction of spending paid by cash, debit cards, mobile payments, and credit cards. Spending and Log(spending) are the absolute and 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 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.

	(1)	(2)	(3)	(4)	(5)	
	Cash usage	Debit usage	Mobile usage	Credit usage	Spending	Log
PriorCashDependence $\times$ Post	-0.392***	0.335***	0.003***	-0.014***	297.295*	
	[-315.87]	[252.71]	[11.22]	[-21.95]	[1.77]	
Consumer Fixed Effects	Yes	Yes	Yes	Yes	Yes	
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	
R^2	0.509	0.518	0.363	0.373	0.435	
No. of Observations	4,001,967	4,001,967	4,001,967	4,001,967	4,001,967	4

Table 7: **Digital payments and spending in the sample excluding November 2016 to January 2017**

This table estimates the longer-term 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, excluding the first three months following the Demonetization announcement (November 2016, December 2016, and January 2017). 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 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.

	(1) Cash usage	(2) Spending	(3) Log(spending)
PriorCashDependence $\times$ Post	-0.305***	225.099***	0.337***
	[-367.81]	[24.99]	[122.43]
Consumer Fixed Effects	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes
R^2	0.640	0.447	0.603
No. of Observations	6,509,979	6,509,979	6,509,979

Table 8: **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. The data are at the individual-product category-month level from April 2016 to September 2017. Amount, Quantity, Unit Price, and Use offer are the spending amount in rupees, the quantity of goods purchased, the unit price of goods purchased, and an dummy indicating promotional offers are used (measured as the actual price paid being lower than the listing price) by a given consumer on a given category in a given month, respectively. 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.

	Amount		Quantity		Unit Price		Use Offer	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
PriorCashDependence × Post	10.828***	19.255*	0.084*	0.281	1.932***	1.616***	-0.002***	-0.004***
	[2.86]	[1.84]	[1.69]	[1.56]	[23.30]	[21.13]	[-4.87]	[-9.72]
Consumer Fixed Effects	Yes	No	Yes	No	Yes	No	Yes	No
Consumer-Category Fixed Effects	No	Yes	No	Yes	No	Yes	No	Yes
Category-Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.111	0.432	0.139	0.434	0.558	0.682	0.407	0.649
No. of Observations	47,182,408	47,182,408	47,182,408	47,182,408	47,182,408	47,182,408	47,182,408	47,182,408

Table 9: **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 with amount at least as large as the 90th percentile (467 rupees) in the distribution of receipt size from April 2016 to October 2016. The data are at the individual-month level from April 2016 to September 2017. 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 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.

	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	-0.333***	234.521***	0.516***	-0.215***	162.003*	0.030***
	[-403.10]	[67.87]	[182.27]	[-137.24]	[1.76]	[6.24]
Consumer Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.663	0.595	0.574	0.547	0.435	0.485
No. of Observations	4,836,072	4,836,072	4,836,072	2,808,198	2,808,198	2,808,198

Table 10: **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 from April 2016 to September 2017. 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 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.

	Log(spending)				
	Full	Existing users		New users	Non-users
	(1)	(2)	(3)	(4)	(5)
PriorCashDependence × Post	0.300***	0.230***	0.247***	0.410***	0.295***
	[123.90]	[13.40]	[13.49]	[49.19]	[113.02]
after_credit_amt_pct_before			0.066***		
			[2.74]		
Consumer Fixed Effects	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes
R^2	0.593	0.523	0.523	0.504	0.586
No. of Observations	7,644,270	249,668	249,668	551,031	5,770,361

Table 11: **Is increased spending driven by moving grocery purchases 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 from April 2016 to September 2017. Cash usage is the fraction of spending paid by cash. Total (grocery, non-grocery) spending is the inverse hyperbolic sine transformed level of total (grocery, non-grocery) spending. 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.

	Previous grocery spending $\leq$ 95%				Previous grocery spending $>$ 95%			
	(1) Cash usage	(2) Total spending	(3) Grocery spending	(4) Non-grocery spending	(5) Cash usage	(6) Total spending	(7) Grocery spending	(8) Non-groce spendin
PriorCashDependence $\times$ Post	-0.350***	0.232***	0.357***	-0.088***	-0.309***	0.301***	0.294***	0.134***
	[-195.44]	[41.12]	[43.19]	[-6.95]	[-381.75]	[114.53]	[107.98]	[31.53]
Consumer Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Time Fixed Effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.608	0.569	0.533	0.422	0.626	0.603	0.588	0.411
No. of Observations	1,191,000	1,191,000	1,190,994	1,190,994	6,453,260	6,453,270	6,453,253	6,453,25