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The Indian banknote demonetization in 2016 was one of the most significant international events of that year. Overnight, 86 percent of Indian currency in circulation was declared invalid unless exchanged for new bills. The sudden and unexpected demonetization constituted a large shock to the entire Indian economy. One effect of the ensuing cash shortage was a large and sustained increase in the adoption and usage of digital payments. We use detailed sales data consisting of more than two and a half million transactions from a leading Indian online retailer to empirically investigate the effects of payment digitization on the online retail industry. We take advantage of the demonetization as a source of exogenous variation that induced a subset of consumers to switch to digital payments from more commonly used cash-on-delivery payments. We show that consumers who switch to digital payments maintain their purchase frequency but spend more and are less likely to return their purchases. Our findings show that firms in emerging markets may enjoy gains from consumer demand in addition to operational gains resulting from payment digitization.

Key words: cash on delivery; emerging markets; online retail; product returns; supply chain management

1. Introduction

The Indian banknote demonetization was one of the most significant international events of 2016. Narendra Modi, the Indian prime minister, announced the demonetization in an unscheduled live televised address on November 8, 2016, declaring that the use of all 500- and 1,000-rupee banknotes would be invalid past midnight, and announcing the issuance of new 500- and 2,000-rupee banknotes. Overnight, 86 percent of Indian currency in circulation ceased to be legal tender. The stated aim of the demonetization was the elimination from the economy of illicit cash—funds connected to illegal activities that were held in cash to avoid government monitoring. The sudden and unexpected nature of the announcement and the weeks-long cash shortage that followed created significant disruptions throughout the economy.

The cash shortage had a particularly interesting impact on the online retail industry. As in several other major emerging markets, online shoppers in India typically have the option to pay for their purchases using digital payments (e.g., credit cards, debit cards, digital wallets) or to opt for cash-on-delivery (COD). Cash-on-delivery is a payment method in which customers pay for products with cash at the time of receipt. Its use predates e-commerce, but remains popular in the online retail industries of several large emerging markets, including those of China, Russia, Brazil, and India. As many as 60 percent of online transactions in India are conducted using COD (Nair 2013). Following the demonetization and the ensuing cash shortage, large numbers of Indian customers switched from using COD to using digital payments (Agarwal et al. 2018). This shock to payment choice presents an opportunity to study the effect of the mode of payment on outcomes for online retailers in emerging markets.

Online retail has been growing rapidly in emerging markets. The size of the online retail sector in nine major developing countries—Brazil, Mexico, South Africa, Russia, Turkey, China, Saudi Arabia, Indonesia, and India—could collectively increase from an annual turnover of USD 731 billion in 2016 to USD 2.5 trillion by 2025, a 13 percent annual growth rate (Credit Suisse 2016). The main driver of this growth is the increase in internet access, particularly for lower-income groups in emerging markets. The rise in smartphone ownership also plays an important role in this shift.

The e-commerce industry in India has by itself been growing at an unprecedented rate. Its size grew from USD 14 billion in 2014 to USD 38.5 billion in 2016—a compound annual growth of 40 percent (Foundation 2018). Online retail is the fastest-growing segment, having grown at an average annual rate of about 56 percent (PwC India 2015). The online retail market in India is estimated to be worth about USD 17.8 billion in gross merchandize value (GMV) as of 2017 and is estimated to have increased by 60 percent to USD 28 billion in 2018 (Foundation 2018). Flipkart, considered the largest e-commerce venture in India, started in 2009 with a GMV of USD 10 million, and grew to USD 1 billion in 2014 and USD 4 billion in 2015 (Sharmal 2016). Snapdeal, another large Indian e-commerce company, grew by 500 percent between 2012 and 2013 and posted a GMV of USD 2.2 billion in May 2015 (Singh 2016).

Cash-on-delivery is a popular payment choice for online retail in India for several reasons. First, the penetration of digital payments such as credit cards, debit cards, or mobile wallets is low. In 2016, less than 25 million credit cards were active in the country (RBI 2017). In contrast, there were 453 million credit cards in the US by the end of 2016 (Statista 2016). Second, even customers with access to digital payments may be reluctant to employ them when buying online because of a lack of trust or security concerns. This lack of trust by customers in online sellers further increases the attraction of the COD option, as payment is contingent on delivery and often inspection of goods.

While COD offers some benefits to customers, it is a relatively costly payment method for merchants to process. A customer who opts for COD pays the delivery person at the time of receipt, who transfers the funds to a supervisor, who then remits the funds to the e-commerce firm. The required level of interaction between customers and delivery staff often results in multiple delivery attempts for a single order. Time between payment and receipt by the firm of funds is typically three to five days, depending on the shipping location. In some extreme cases, the settlement period can last as long as three weeks.

There is anecdotal evidence that COD purchases are associated with a higher instance of returns, as buyers are less committed to the purchase than if they had paid in advance (Das 2014). In most cases, customers can decline delivery at the door for free, requiring the delivery person to return the product upstream. As a result, there is little potential for regret costs for customers who make impulse purchases. Returns can hurt firms not only by way of logistics costs of round-trip product delivery, but also through inventory costs of having unproductive inventory in the delivery pipeline and potential reordering from upstream firms in the supply chain. Both of these costs can be amplified as transit time increases, especially in markets like India, with vast land areas and relatively poor transport infrastructure. According to one Indian e-commerce company's estimates, COD transactions add about three percent in additional costs, and the costs can increase by as much as 30 percent with returns (Nair 2013).

The Indian demonetization of 2016 was thus of particular relevance for online retailers, who saw a marked and sustained increase in the adoption of digital payments in the periods thereafter (Agarwal et al. 2018). Contributing to this shift was the prolonged cash shortage many Indians experienced following the demonetization. Related research has shown that most consumers who adopted digital payments due to the demonetization tended to maintain their level of digital payment usage well beyond the cash shortage (Chodorow-Reich et al. 2018).

In typical settings, a causal link between the mode of payment (e.g. cash versus card) and shopper behavior is difficult to establish, as these decisions are possibly jointly determined; for instance, a customer may choose COD for smaller purchases but use her credit card for larger purchases. The shock from the demonetization provides rare exogenous variation in online shoppers' payment choices that can be used to measure the effect of the mode of payment on purchase outcomes, such as basket sizes and the frequency of product returns.

We obtain data consisting of more than two and a half million transactions from a leading online apparel retailer in India. Our period of study covers a span of six weeks before and after the demonetization. The panel structure of the data allows us to identify which customers are likely to have switched payment methods because of the demonetization, and to measure the impact of the change on their behavior.

We find that customers who switch to digital payments conduct as many transactions as those who continue using cash; however, they spend more on each transaction and are less likely to return their purchases. Our analysis of the data suggests that increased transaction sizes derive both from an increase in the number of items in each transaction as well an increase in the average price of products sold. Furthermore, differences in both the prices of products sold and the rate of product return are broadly consistent across product categories.

We conduct robustness checks of our analysis and find that our estimates are robust to alternative treatment date specifications, group definitions, as well as the exclusion of time series information. Our analysis of alternative treatment date specifications suggests an interesting difference in how purchase amounts and return rates vary with payment choice; our causal identification strategy appears to be less critical for return rates than it is for purchase amounts. Moreover, we find that the effect of payment choice on basket sizes and return rates are most pronounced for consumers with the lowest pre-demonetization average order values.

While digital payments in online retail are the norm in most advanced economies, online sellers in many emerging markets are in the early stages of a shift from cash-based payments to digital payments. Our findings show that these firms may enjoy gains from consumer demand on top of operational gains resulting from payment digitization.

The remainder of the paper is organized as follows. Section 2 reviews the related literature on payment choice, consumer behavior, and firm outcomes. Section 3 introduces the data and background information on the institutional setting. Section 4 outlines the estimation approach and presents the results of our analysis. Section 5 presents results of robustness checks and additional findings concerning heterogeneous treatment effects. Section 6 concludes, points out limitations of our study, and provides directions for future research.

2. Related literature

In this section, we provide a review of related literature concerning modes of payment and online retail transactions. We touch on streams of research in operations management, consumer psychology, quantitative marketing, and macroeconomics. Within each stream, we cite the most closely related papers, while acknowledging that the full extent of the related literature includes many more studies.

Prior research has put forth several psychological mechanisms through which a buyer's mode of payment may influence her purchase decisions. Across several studies and hypothesized mechanisms, credit card payments have been shown to be associated with higher spending levels (Hirschman 1979; Soman 2001; Prelec and Simester 2001). These studies show that the effect persists regardless of whether credit cards are understood to relax consumers' liquidity constraints. Even mere cues associated with credit cards have been found to enhance the probability, speed, and magnitude of spending (Feinberg 1986).

One stream of research in particular identifies how the *pain of payment* may result in consumers preferring to use payment modes such as credit cards, which are relatively decoupled from consumption, over cash, which is more tightly coupled to consumption (Prelec and Loewenstein 1998). This pain of payment has been found to make impulse purchases less likely; consumers were found to be more likely to purchase unhealthy foods when using credit cards rather than cash (Thomas et al. 2010). Relatedly, cash payments have been found to result in strongler feelings of ownership due to an increase in the perceived investment in an object (Kamleitner and Erki 2013).

Research on payment choice, while often agnostic to the institutional settings of transactions, has not specifically addressed the tradeoffs that may exist for customers choosing digital versus COD payments when shopping online. However, work that examines the decoupling of payment and consumption may be informative, in that digital payments are processed earlier than COD and are thus less coupled to consumption. Consumption, for instance, has been shown to be more enjoyable for decoupled payments (Gourville and Soman 1998; Raghubir and Srivastava 2008)—leading perhaps to a lower probability of returned purchases in our setting.

There also exists a stream of literature that examines customer preferences for payment choices, holding transaction characteristics constant. A consistent finding is that even credit and debit card holders have a preference for cash usage, particularly for small-value transactions (Hancock and Humphrey 1997; Abdul-Muhmin 2010; Wakamori and Welte 2017; Cohen and Rysman 2013; Arango et al. 2015). These results seem broadly consistent in developed countries other than the US, where carrying over credit card balances is more common (von Kalckreuth et al. 2013; Bagnall et al. 2014; Wang and Wolman 2016). Within the US, higher income has been seen to lead to more credit card use (Carow and Staten 1999; Humphrey 2004; Klee 2008; Cohen and Rysman 2013; Koulayev et al. 2016). Whereas much of the payment choice literature seeks to explain the prevalence of cash in developed economies with established card payment systems, research on payment choice in emerging economies has found that mobile phones have enabled the proliferation of digital payments (Bech et al. 2018).

There have been mixed results as to the benefit to sellers of more customers adopting digital payments. Some results suggest that merchant costs would decline if only cash transactions existed (Borzekowski and Kiser 2008; Briglevics and Shy 2014), whereas analyses of economy-wide welfare have found or assumed that electronic payments are cost-saving for societies (Humphrey et al. 2001; Bergman et al. 2007). The bulk of this research assumes demand and spending to be invariant to payment choice and focuses on the infrastructure and contractual costs of accepting digital payments. The literature has also remained largely silent on cash payments in online retail in emerging markets, within which processing costs may dwarf those for digital payments.

In addition to seeking to establish a link between payment choice and purchase outcomes, our research examines the effects of payment choices on the likelihood of product returns. Anderson et al. (2009) study the option value of returns for consumers using a structural modeling framework. Specific reasons for returns have also been explored in prior research, especially those relating to poor match in taste and fit (e.g. Anderson et al. 2009, Altug and Aydinliyim 2016; Gallino and Moreno 2018). Previous work has illustrated how free return policies can benefit customer satisfaction and lifetime value (Petersen and Kumar 2009; Bower and Maxham III 2012), whereas other work has examined how customers can be charged for returns in competitive settings (Wood 2001; Shulman et al. 2011). To our knowledge, the impact of payment choice on the likelihood of product return has not been studied in the existing literature.

We contribute to these streams of research by examining the impact of payment choice in an understudied context: online retail in emerging markets. Our empirical setting is representative of online sectors in many economies around the world, where the fast growth of e-commerce has outpaced the adoption of digital payments. The consequent predominance of cash payments for online purchases in these markets presents an interesting empirical setting in which to examine the relationships between payment choice and purchase outcomes established in the related literature. In addition, the exogenous shock produced by the 2016 Indian demonetization provides a unique opportunity to measure the impact of payment choice on purchase outcomes in actual retail settings. In the following section, we describe the data we use for analysis and provide relevant details on the empirical setting.

3. Background and data

We obtain transaction data from a leading online fashion retailer in India. By the 2016 demonetization, the company had been in operation for over five years. The data span the period September 29 to December 28, 2016, which is about six weeks before and after the demonetization, which occurred on November 8. We observe the date of each transaction, the stock-keeping unit (SKU) of each item sold, and a hashed customer ID that allows us to track individuals over time. We also observe payment choice (COD or digital) and whether an item is returned or kept by the customer. As coded in the data, a return may represent either a refusal of the order at the time of delivery or a later retrieval of the product by the firm.

The data also include each SKU's product category (e.g. t-shirt, casual shoes, etc.) as well as product-specific gender information (men, women, boys, girls, unisex). For each transaction, we observe the following variables related to pricing: transacted price (*Price*) is the final selling price of each product; merchant recommended price (*MRP*) is the "original price" listed online; and discount (*Discount*) is the amount taken off the MRP.

In total, the data set contains information on 4,528,324 items sold, 2,522,869 transactions, 301,131 unique SKUs, and 1,485,795 customers. The average price of products sold is INR 914.35 (about USD 13) with a standard deviation of INR 816.43 (about USD 11.5). A box plot of prices in the 11 product categories with the highest sales can be found in Figure 1. Cash-on-delivery was used in 63.34 percent of transactions, consistent with reports on the overall usage of COD in the country. Overall, 21.34 percent of transactions were marked returned, which is also consistent with industry norms.

Figure 2 shows daily sales volumes and transaction counts, respectively, before and after the demonetization. Total daily sums are displayed together with cash and digital payment choice components. Sales decline sharply following the demonetization, with most of the decline attributed to cash transactions. Digital payment transactions, in contrast, appear relatively stable. Consistent with reports on overall economic activity in India at the time, sales return to pre-demonetization levels roughly three weeks after the demonetization (Agarwal et al. 2018).

We present the ratio of cash to digital payments in Figure 3, again by both sales and transaction counts. There seems to be a pronounced decline in the proportion of sales paid for with cash, followed by an uptick and a further decline. Figure 4 plots the number of first-time users of digital payments in our data set. The data clearly show that the demonetization produced a dramatic increase in the adoption of digital payments for the firm, which persists well beyond the demonetization. The overall pattern in the shift to digital payments following the demonetization

Figure 1 Prices of different product categories

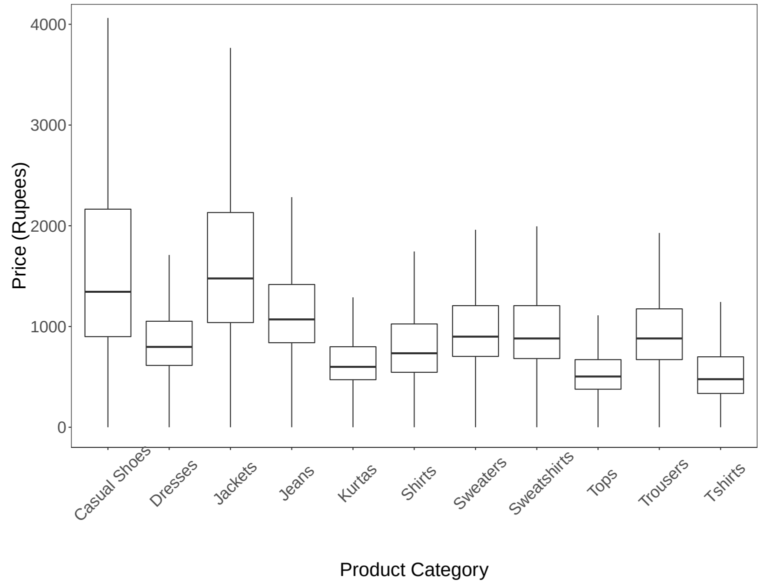
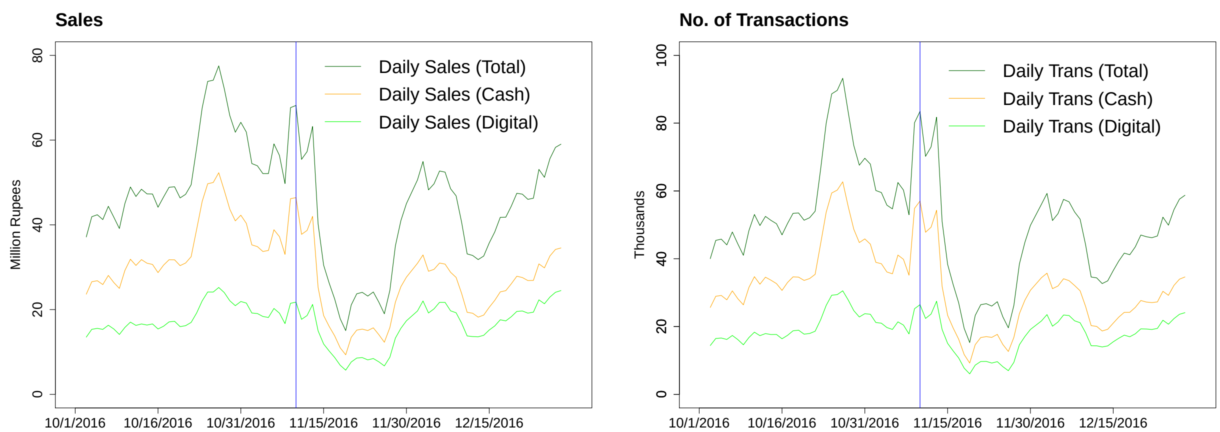


Figure 2 Sales activity before and after the demonetization

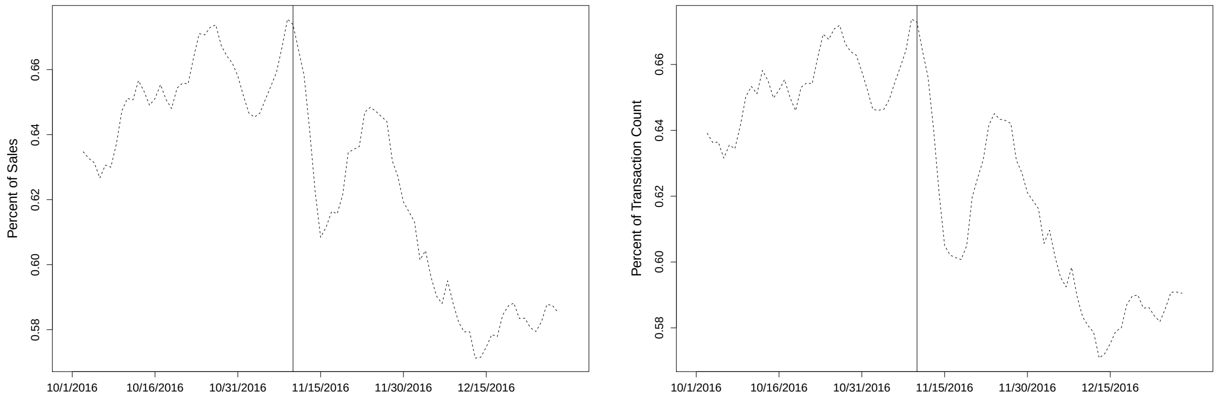


Note: Data are smoothed by taking a five-day moving average.

is consistent with that found by Agarwal et al. (2018) in their analysis of sales data from multiple Indian retailers.

The extent of the shift to digital payments may have been amplified by the prolonged cash shortage in India during the last weeks of 2016. The demonetization required all old banknotes to be deposited or exchanged in banks by the end of the year. However, following the announcement on November 8, the government imposed a daily limit of INR 2,000, increased to INR 2,500 on November 15, on how much cash in new banknotes each individual could withdraw. Long lines at banks were a common sight during the last weeks of 2016. Figure 5 illustrates the relative availability of currency during this period.

Figure 3 Proportion of COD sales transactions pre- and post-demonetization



Note: Data are smoothed by taking a five-day moving average.

Figure 4 Digital payment adopters

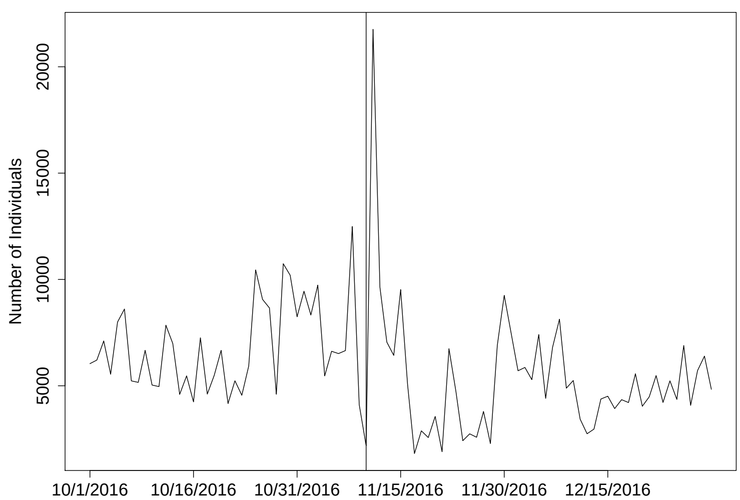
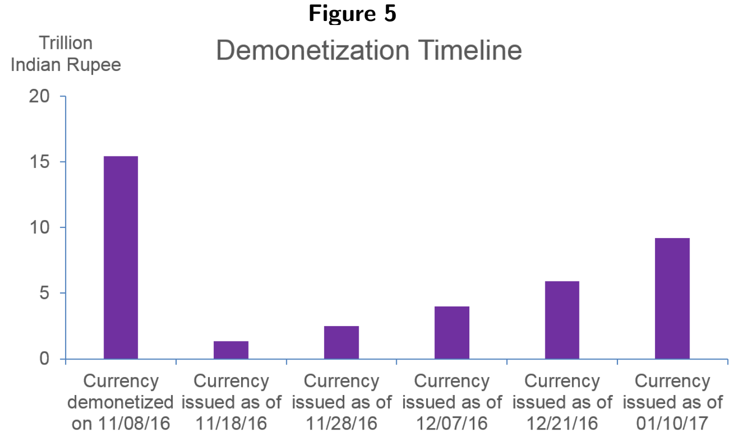


Figure 5



Source: Reserve Bank of India

We run a series of regressions to measure the overall correlations in the data between our variables of interest prior to the demonetization. Table 1 displays estimates of regressions run at the transaction and item levels, with and without date and customer fixed effects. These regressions, in addition to all that follow, include standard errors that are clustered at the customer level. Column 1 shows that, overall, digital payments are associated with higher basket sizes. However, adding controls (Column 2) shows that this relationship disappears when measured within consumers. Along the same lines, Columns 3 and 4 show that on average, orders paid for with digital payments contain more items; however, controlling for customers, this relationship is also muted.

Item-level regressions (Columns 5-8) are more consistent in overall correlations in the data with and without controls. Items bought with digital payments tend to be higher-priced, and are less likely to be returned. These measurements provide a sense of overall patterns in the data between our variables of interest, and perhaps are suggestive of certain shopper behaviors, but cannot identify causal relationships. The related literature provides several theories that may jointly result in these patterns.

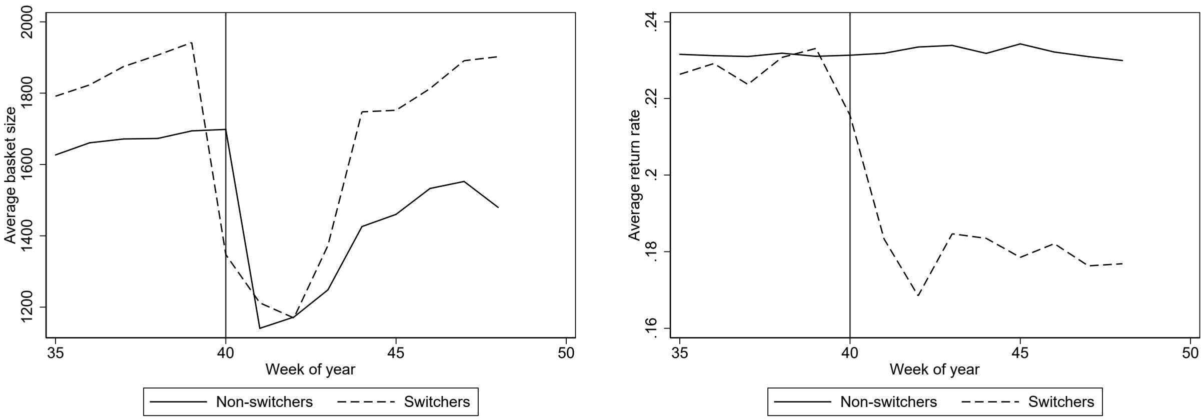
Table 1 Descriptive regressions using data from pre-demonetization period

VARIABLES	(1) Basket size	(2) Basket size	(3) No. of items	(4) No. of items	(5) Item price	(6) Item price	(7) Return rate	(8) Return rate
Digital	208.4**	-177.9	0.223**	-0.307	3.102	9.137***	-0.0496***	-0.0483***
	(104.0)	(218.3)	(0.0987)	(0.207)	(6.844)	(3.160)	(0.000545)	(0.00150)
Constant	1,734***	2,011***	1.914***	2.240***	906.0***	841.1***	0.231***	0.231***
	(1.965)	(77.79)	(0.00182)	(0.0736)	(0.954)	(1.131)	(0.000342)	(0.000537)
Date FE	No	Yes	No	Yes	No	Yes	No	Yes
Customer FE	No	Yes	No	Yes	No	Yes	No	Yes
Observations	1,167,807	579,958	1,167,807	579,958	2,317,934	2,003,493	2,317,934	2,003,493
R-squared	0.000	0.762	0.000	0.762	0.000	0.505	0.003	0.248

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

In our sales data, of the 395,223 customers who used only cash payments before the demonetization, 76,388 make a purchase after the demonetization, and of that group, 18,720 used digital payment methods. In the following section, we describe how we take advantage of the exogenous change in payment choice ushered in by the demonetization to measure the effect of payment choice on purchase outcomes.

Figure 6 Average Basket Size and Return Rate by Group



4. Data analysis

The primary objective of our analysis is to measure the impact of payment choice on online retail outcomes, including average basket sizes and product return rates. The key variation in the data we exploit in this analysis is that the demonetization caused some consumers, but not others, to switch their payment choices from cash to digital. As seen in Figures 3 and 4, the demonetization appears to have significantly skewed the overall composition of payment choices for the retailer toward digital payments from COD and caused a substantial increase in the adoption of digital payments.

We initially restrict our attention to consumers who only used COD prior to the demonetization, and define two groups: *switchers*—those who use digital payments exclusively after the demonetization, and *non-switchers*—those who continue using COD. We exclude from our analysis customers who do not fit these patterns: for instance, customers who used digital payments before the demonetization and used COD at least once afterwards. Figure 6 displays average weekly values for key outcome variables. In our later robustness tests, we explore how expanding the definition of our two groups affects our estimates.

Two possible factors determine whether a customer switches to digital payments. The first is availability or ownership of digital payment methods: a customer may simply not have access to digital payment methods and thus be constrained to using cash. Note that this only applies to non-switchers who consistently use cash throughout the sample period. The second possible factor is that some customers may have had little cash on hand during the demonetization and thus were more impacted by the cash shortage than others. Because the demonetization was unexpected, and was planned as such to prevent consumers from adjusting their cash stocks preemptively, we anticipate any selection bias to be minimal.

In order to mitigate selection between the two groups, we use propensity score matching using pre-demonetization values for: number of transactions, average basket size, return rate, and item gender.[1] Table 2 shows summary statistics for users falling into either group. Differences in average basket size, number of orders, and gender are significantly different between groups. Table 3 contains estimates of the logit regression used in our matching. Table 4 shows summary statistics of the matched samples. Differences between the four variables are insignificant for the matched samples.

Table 2 Summary statistics before pruning

Variable		Non-switchers	Switchers	Difference C - T	P-value
Average basket size	Mean	1720.27	1808.95	-88.68	0.00%
	Std. Error	4.46	13.29	13.26	
Number of orders	Mean	1.55	1.40	1.53	0.00%
	Std. Error	0.00	0.01	0.00	
Return rate	Mean	0.23	0.23	0.004	17.76%
	Std. Error	0.00	0.000	0.00	
Gender (1 = Woman)	Mean	0.42	0.45	-0.02	0.00%
	Std. Error	0.00	0.00	0.00	
N		83,953	10,930		

Table 3 Propensity score logit regression, matching

Variable	Switcher
Average basket size	0.0001***
	(0.00001)
Number of orders	-0.1864***
	(0.0124)
Return rate	-0.0429
	(0.0323)
Gender (1 = Woman)	0.1436***
	(0.0219)
Constant	-1.9152***
	(0.0266)
Observations	94,883
Log Likelihood	-33,726.19

[1] Appendix C contains estimates without matching, which are broadly consistent with our matching results.

Table 4 Summary statistics after pruning

Variable		Non-switchers	Switchers	Difference C - T	P-value	Bias Reduction	Variance Ratio Unmatched	Variance Ratio Matched
Average basket size	Mean	1796.28	1808.95	-12.67	50.51%	85.7%	1.16*	0.96*
Number of orders	Mean	1.39	1.40	-0.01	39.11%	93.6%	0.64*	1.02
Return rate	Mean	0.23	0.23	0.00	94.81%	93.5%	1.01	0.97
Gender (1 = Woman)	Mean	0.44	0.45	-0.01	24.26%	70.2%	1.04*	1.01
N		10,930	10,930					

We estimate the following model using our matched samples to measure the effects of payment choice on outcomes:

$$y_{id} = \alpha + \beta Switcher_i + \gamma Demo_d + \delta Switcher_i \times Demo_d + \theta X_{id} + \epsilon_{id} \tag{1}$$

where the dependent variable y_{id} is the order size, the number of transactions, or the likelihood of product return. The independent variable, $Switcher_i$, indicates whether the individual switched to digital payments after the demonetization. The interaction term, $Switcher_i \times Demo_d$, indicates whether day d occurs after the demonetization for the switcher group. X_{id} are fixed effects that control for customer and date. Finally, ϵ_{id} is the error term. The parameter of interest in each regression is δ.

The main results of our analysis are presented in Table 5. In this table, the $Demo_d$ period is defined as 9 Nov 2016-28 Dec 2016 and the remaining data is prior to the demonetization, 29 Sep 2016-8 Nov 2016. For each outcome variable, we estimate two specifications: one without customer and date fixed effects and one that includes them. Our preferred specification includes these fixed effects. For basket size (Columns 1 and 2), we find that switchers spend on average INR 133.70 more than non-switchers. In looking at return rates (Columns 3 and 4), we find that switchers have a probability of returning an item that is lower by over five percentage points than non-switchers. Counting daily transaction totals between the two groups, we find no significant difference in relative conversion rates following the demonetization (Columns 5 and 6).

Our primary analysis suggests that the firm experiences demand-side benefits when customers switch from COD to digital payments. Not only do customers tend to spend more, but they also tend to return fewer items while keeping the total number of orders constant. In the following auxiliary analysis, we exploit product-level information in the data to pinpoint how these benefits are spread across product categories. We examine whether the increase in basket size comes from an increase in the number of products per order, or whether the increase in demand disproportionately applies to certain product categories.

Table 6 contains results from regressions of the form in Eq 1, but for outcome variables related to basket composition. Columns 1-2 contain estimates for the number of items in each order, a

Table 5 Results for matched samples

VARIABLES	(1) Basket size	(2) Basket size	(3) Return rate	(4) Return rate	(5) No. of Trans.	(6) No. of Trans.
$Demo_d$	-432.0***		0.00208		-128.6***	
	(15.25)		(0.00352)		(49.17)	
$Switcher_i$	24.49		-0.00155		3.281	3.281
	(20.26)		(0.00335)		(54.09)	(20.37)
$Demo_d \times Switcher_i$	161.3***	133.7***	-0.0508***	-0.0556***	-50.55	-50.55*
	(23.00)	(22.26)	(0.00493)	(0.00547)	(69.54)	(26.19)
Constant	1,822***	1,620***	0.230***	0.231***	474.7***	396.9***
	(14.34)	(5.251)	(0.00237)	(0.00118)	(38.25)	(9.053)
Time and Customer FE	NO	YES	NO	YES	NO	YES
Observations	62,087	62,087	113,355	113,355	162	162
R-squared	0.018	0.503	0.003	0.193	0.116	0.937

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

transaction-level outcome variable. Switching to digital payments appears to have a small but significant effect on the number of items that payment choice switchers buy. Columns 3-4, meanwhile, contain estimates for item price, a product-level outcome. Prices for individual items switchers buy were also relatively higher post-demonetization. This implies that customers bought slightly more items per order and opted for more expensive options.

Inspecting category-specific differences in transacted prices and return rates (see Figures 7 and 8) suggests that the measured effects are not specific to particular product categories. In these figures, we display the relative levels of each outcome for the firm's top 11 product categories. Despite the large diversity between categories, we observe similar differences in prices of items sold and return rates between them for our two groups.

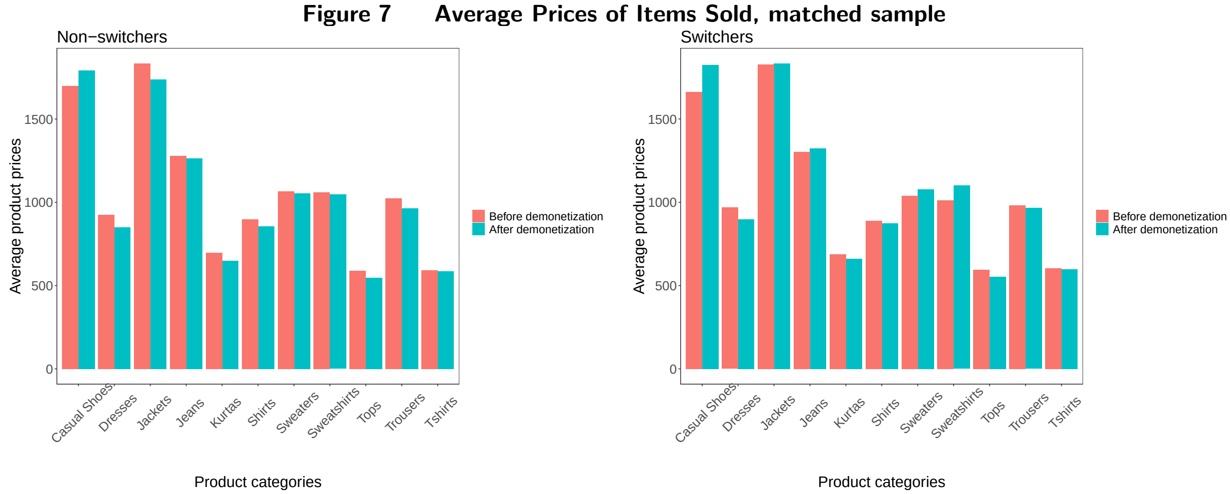
Our findings on the impact of payment choice on basket size are consistent with the literature on *pain of payment* (e.g., Prelec and Loewenstein 1998). According to this literature, non-cash transactions decouple payment from consumption, which results in higher purchase likelihoods and higher purchase amounts. Our analysis suggests that consumers induced to using digital payments in our empirical setting tend to have more items in their purchase baskets, and these items also tend to be higher-priced. Predictions from the literature also suggest relatively larger effects for impulse and discretionary purchases (e.g., Thomas et al. 2010); demand faced by online fashion retail may be particularly sensitive to these effects. While these effects have been observed in laboratory settings, we provide evidence from an actual retail setting, as well as a measurement of the magnitude of the effects.

Table 6 Auxiliary regressions, matched sample

VARIABLES	(1) No. of items	(2) No. of items	(3) Item price	(4) Item price
$Demo_d$	-0.476***		-3.821	
	(0.0141)		(7.712)	
$Switcher_i$	0.0241		1.423	
	(0.0189)		(9.259)	
$Demo_d \times Switcher_i$	0.0917***	0.0721***	47.91***	41.00***
	(0.0210)	(0.0206)	(11.41)	(11.46)
Constant	2.035***	1.809***	895.2***	895.7***
	(0.0133)	0.00485	(6.592)	2.478
Customer FE	NO	YES	NO	YES
Date FE	NO	YES	NO	YES
Observations	62,087	62,807	113,355	113,355
R-squared	0.029	0.473	0.001	0.441

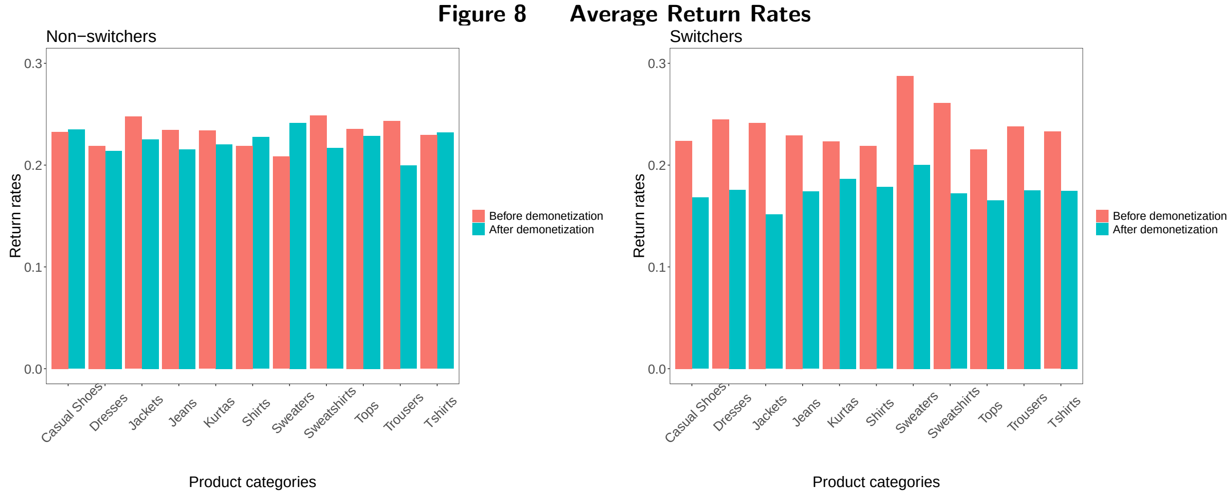
Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Figure 7 Average Prices of Items Sold, matched sample



Our findings on the effect of digital payment adoption on product returns complement the previous research on returns, which to our knowledge has not considered the relationship between product returns and payment choices. Our estimates show that consumers adopting digital payments are less likely to return their purchases by over five percentage points. Our results suggest that online sellers offering COD may benefit greatly from encouraging digital payment adoption. In the following section, we present the results from a series of robustness checks and explore how different consumer subgroups responded to the demonetization.

Figure 8 Average Return Rates



5. Robustness Checks and Heterogeneity

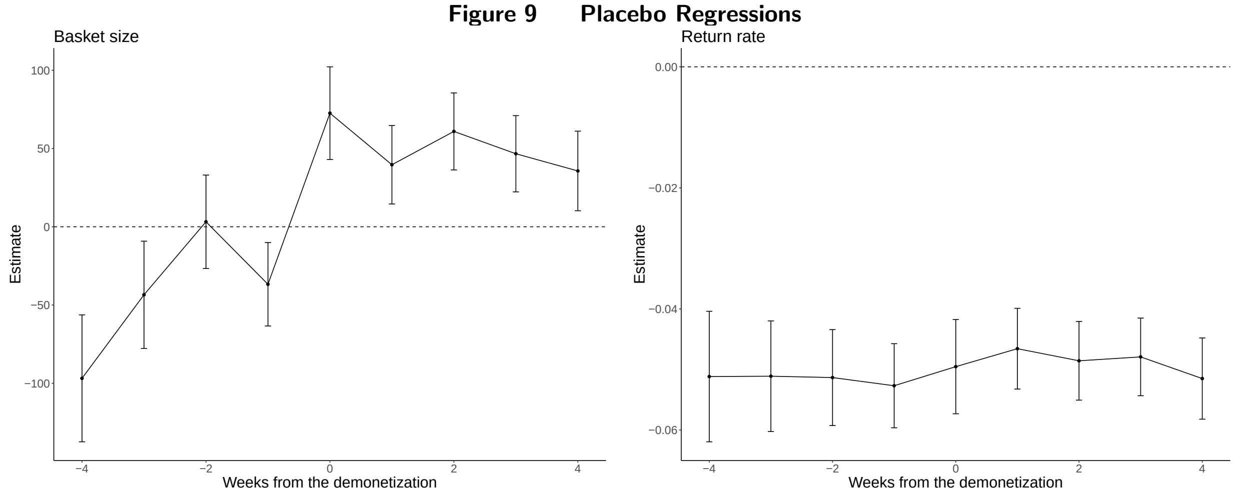
We carry out several robustness checks to validate our main results. First, we measure the sensitivity of our results to the treatment date specification. Second, we test for the robustness of our results to alternative group definitions. Third, we run our baseline specification ignoring time series information as in Bertrand et al. (2004). We use this specification to investigate heterogeneity in our measured effects according to average pre-demonetization basket sizes and return rates. We also note that the estimates in Table 1 imply that our estimated effects run counter to the overall tendency in the data for basket sizes to be lower for digital payments, controlling for customer fixed effects.

We conduct a set of placebo regressions to test for sensitivity around the demonetization date.[2] We may expect the effects of the demonetization to occur or persist well beyond the actual date of the event. Consumers have varying purchasing schedules and cash stocks, such that the switch to digital payments due to a cash shortage may happen well beyond the announcement of the demonetization. We run versions of our baseline specification for each of the main dependent variables, basket size and return rate, using synthetic demonetization events. We construct switcher and non-switcher groups based on synthetic events at +/- 7, +/- 14, +/- 21, and +/- 28 days of the November 8, 2016 demonetization. The counterfactual effect patterns are presented in Figure 9, including 95% confidence interval bars. Actual estimates are presented in Tables A.1 and A.2 in the Appendix.

The placebo regressions for revenue as a dependent variable provide supporting evidence for our identification strategy. The estimates show that our measured effect on basket sizes holds for periods after the demonetization, but not before. In fact, consumers who switch to digital payments

[2] In order to maintain stability in the group definitions, we use unmatched groups for this analysis.

Figure 9 Placebo Regressions



before the demonetization appear to have smaller basket sizes on average. This pattern is consistent with the preliminary evidence presented in Table 1.

The placebo regressions for return rates as a dependent variable suggest a much more stable relationship between payment choice and the likelihood of return. Consumers who switch to digital payments are less likely to return items, regardless of whether this change was exogenously determined. Basket sizes, on the other hand, seem much more likely to be jointly determined with payment choice; i.e. when free to choose payment methods, consumers may prefer to use COD for larger purchases.

In our next set of robustness checks, we explore the sensitivity of our estimates to our group definitions. Table 7 contains the results of these robustness checks. We report three pairs of regressions, all of which contain the full set of regressors, corresponding with Columns 2 and 4 of Table 5. All of these regressions use ummatched samples, as the specified alternative group definitions are undefined for the matched samples. Columns 1 and 2 contain regressions that expand the non-switchers group to include customers who only pay with digital methods within the sample. Columns 3 and 4 contain regressions that exclude non-switchers who are not observed after the demonetization. Columns 5 and 6 expands the non-switcher group to include all customers who do not conform to the switcher group definition. We find that our results are broadly insensitive to these changes in group definitions.

In our final series of robustness checks, we replicate our main analysis ignoring time series information as in Bertrand et al. (2004). We take averages of our key outcome variables for each customer within pre- and post-demonetization.[3] Consequently, each customer has at most two observations in the adjusted data. These results are shown in Table 8. Once again, our estimates are consistent with those in our baseline specification.

[3] This is not applicable for our regression of transaction counts.

Table 7 Alternative group definitions, unmatched sample

	Digital non-switchers		Exclude dropouts		Broad non-switchers	
	(1)	(2)	(3)	(4)	(5)	(6)
VARIABLES	Basket size	Return rate	Basket size	Return rate	Basket size	Return rate
$Demo_d \times Switcher_i$	59.46***	-0.0514***	77.32***	-0.0495***	83.67***	-0.0496***
	(16.77)	(0.00395)	(16.90)	(0.00406)	(23.30)	(0.00395)
Constant	1,683***	0.214***	1,527***	0.232***	1,752***	0.213***
	(0.252)	(3.47e-05)	(0.490)	(8.99e-05)	(0.228)	(0.000208)
Date FE	YES	YES	YES	YES	YES	YES
Customer FE	YES	YES	YES	YES	YES	YES
Observations	990,896	2,793,626	513,957	1,106,066	1,522,853	3,914,820
R-squared	0.903	0.264	0.518	0.257	0.888	0.226

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 8 Ignoring time series information, matched sample

	(1)	(2)	(3)	(4)
VARIABLES	Basket size	Basket size	Return rate	Return rate
$Demo_d$	-438.6***	-438.6***	0.00460	0.00460
	(14.85)	(14.85)	(0.00443)	(0.00443)
$Switcher_i$	12.67		-0.000278	
	(19.01)		(0.00428)	
$Demo_d \times Switcher_i$	157.4***	157.4***	-0.0577***	-0.0577***
	(21.80)	(21.80)	(0.00614)	(0.00614)
Constant	1,796***	1,803***	0.228***	0.227***
	(13.59)	5.449	(0.00304)	0.00154
Customer FE	NO	YES	NO	YES
Observations	43,720	43,720	43,720	43,720
R-squared	0.021	0.620	0.005	0.500

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

We adopt this specification in exploring heterogeneous treatment effects. We group consumers into terciles according to their average spending and average return rates prior to the demonetization. We run our main specification with outcome variables basket size and return rate for each group separately. Tables 9 and 10 contain the results of this analysis. For each outcome variable, we run separate regressions for consumers in the first ("Low"), second ("Mid"), and third ("High") terciles of their pre-treatment groups, respectively.

Table 9 **Heterogeneous effects, matched sample grouped by pre-treatment average basket size**

	Basket size			Return rate		
VARIABLES	Low	Mid	High	Low	Mid	High
$Demo_d$	293.5***	94.35***	-630.2***	0.00162	-0.00239	0.0145
	(12.44)	(16.31)	(29.54)	(0.0102)	(0.0107)	(0.0117)
$Demo_d \times Switcher_i$	94.16***	62.32***	114.7***	-0.0610***	-0.0509***	-0.0611***
	(21.36)	(23.72)	(42.67)	(0.0142)	(0.0146)	(0.0163)
Constant	483.8***	823.8***	1,835***	0.231***	0.230***	0.221***
	(5.330)	(5.934)	(10.66)	(0.00354)	(0.00366)	(0.00407)
Customer FE	YES	YES	YES	YES	YES	YES
Observations	14,574	14,588	14,558	14,574	14,588	14,558
R-squared	0.569	0.522	0.626	0.509	0.501	0.492

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table 10 **Heterogeneous effects, matched sample grouped by pre-treatment return rate**

	Basket size			Return rate		
VARIABLES	Low	Mid	High	Low	Mid	High
$Demo_d$	-152.0***	130.2***	-39.01*	0.231***	0.0321*	-0.384***
	(19.04)	(29.06)	(21.28)	(0.00625)	(0.0125)	(0.0100)
$Demo_d \times Switcher_i$	99.39***	55.39	91.61***	-0.0543***	-0.0674***	-0.0525***
	(27.92)	(40.96)	(31.41)	(0.00855)	(0.0171)	(0.0137)
Constant	1,138***	796.2***	986.2***	0	0.210***	0.611***
	(6.979)	(10.24)	(7.855)	(0.00214)	(0.00427)	(0.00342)
Customer FE	YES	YES	YES	YES	YES	YES
Observations	24,044	5,160	14,516	24,044	5,106	14,516
R-squared	0.623	0.674	0.628	0.582	0.504	0.667

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

With respect to pre-treatment average basket sizes (Table 9), we find significant coefficients for each subgroup. Switchers with the lowest and the highest average basket sizes seem to increase their basket sizes the most; meanwhile, return rates are relatively similar across groups. Similar comparisons apply for our estimates of heterogeneous effects with respect to pre-treatment return rates (Table 10).

Our analysis in this section suggests that our findings are largely robust to alternative model specifications, treatment date specifications, and group definitions. Our results also seem to be broadly consistent between subgroups of consumers as defined by pre-treatment purchase behavior.

6. Conclusion

In many major emerging markets, the growth of online retail has outpaced the shift from cash-based to digital payments. Consequently, online sellers have had to accept cash-on-delivery to serve large groups of consumers. Online sellers stand to enjoy large cost savings from migrating consumers from COD to digital payments due to the large expenses associated with delivery personnel doubling as cashiers.

Our findings show that there exist substantial demand-side gains from payment digitization in addition to operational gains. Consumers who switch to digital payments due to exogenous reasons tend to buy more expensive items, more items per basket, place higher-valued orders, and return items less often. While these gains occur across customer segments, they are largest for customers within the lowest and highest terciles of average pre-treatment purchase baskets and return rates.

The Indian demonetization of 2016 and the availability of data from a major Indian online retailer provide a rare opportunity to measure the effect of payment choice on purchase outcomes. However, the generalizability of our findings may be limited by our focus on single-firm data. Measurement of the demonetization's effects on different industries and product categories may prove to be a fruitful area for future research.

The available transaction data also limits our availability to identify the precise mechanism that results in the measured gains. Literature on the relationship between payment choice and consumer decision-making provides several possible underlying mechanisms; determining which ones are most relevant in actual retail environments is an interesting area for further study.

Given that digital payment choice is beneficial for sellers, it may also be worthwhile to investigate means by which sellers can encourage consumers to opt for digital payments. Interestingly, the related literature more often documents the reverse practice, e.g., offering discounts to consumers who opt for cash payments. This promises to be an interesting challenge given how purchase decisions and payment choices are jointly determined.

Appendix A: Placebo regression coefficients

Table A.1 Placebo regressions for basket size

Days from Demonetization	Estimate	SE	95% Confidence Interval
-28	-96.83	20.69	[-137.38, -56.28]
-21	-43.47	17.48	[-77.72, -9.21]
-14	3.19	15.22	[-26.64, 33.03]
-7	-36.74	13.60	[-36.39, -10.09]
0	72.57	15.11	[42.96, 102.19]
7	39.63	12.79	[14.56, 64.69]
14	60.92	12.55	[36.32, 85.52]
21	46.65	12.42	[22.30, 70.99]
28	35.66	12.97	[10.24, 61.08]

Table A.2 Placebo regressions for return rate

Days from Demonetization	Estimate	SE	95% Confidence Interval
-28	-0.0512	0.0055	[-0.0619, -0.0404]
-21	-0.0511	0.0047	[-0.0603, -0.0420]
-14	-0.0513	0.0040	[-0.0593, -0.0434]
-7	-0.0527	0.0035	[-0.0596, -0.0457]
0	-0.0495	0.0040	[-0.0573, -0.0418]
7	-0.0466	0.0034	[-0.0399, -0.0532]
14	-0.0486	0.0033	[-0.0551, -0.0421]
21	-0.0479	0.0033	[-0.0543, -0.0415]
28	-0.0515	0.0034	[-0.0582, -0.0448]

Appendix B: Alternative difference-in-differences

In this section, we perform an alternative difference-in-differences (DD) style analysis using control and treatment groups. Our goal is to conform as closely as possible to ideal DD conditions, and thereby produce an additional test of the robustness of our findings. For this analysis, we assign shoppers who have used both COD and digital payments prior to the demonetization to our control group. We assign all other shoppers to our treatment group. The assumption is that the demonetization had no impact on the payment choice of our control group, but may have had an impact on the choices of our treatment group. We also exclude shoppers who use COD exclusively before the demonetization, as they may simply lack access to digital payments. Because not all of the members of this treatment group switch to digital payments as a result of the demonetization, we measure intent-to-treat (ITT) in this formulation.

Table B.1 Alternative DD results

VARIABLES	(1) Basket size	(2) Basket size	(3) Return rate	(4) Return rate
$Demo_d$	-168.1***		0.0104***	
	(47.62)		(0.00102)	
$Switcher_i$	243.3***		0.0270***	
	(39.16)		(0.000785)	
$Demo_d \times Switcher_i$	353.6***	-81.34	-0.0163***	-0.0120***
	(75.30)	(67.11)	(0.00153)	(0.00196)
Constant	1,863***	2,018***	0.182***	0.196***
	(24.94)	(15.75)	(0.000511)	(0.000420)
Time and Customer FE	NO	YES	NO	YES
Observations	660,122	527,225	1,406,297	1,339,006
R-squared	0.000	0.713	0.001	0.155

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Our results are broadly consistent with the main specification we use in the paper. For basket size, we estimate a positive treatment effect; however, the estimated effect becomes insignificant when time and customer fixed effects are added to the model. Our return rate estimate, meanwhile, are directionally consistent with our previous specification. The lower magnitude of the effects are anticipated, given imperfect adoption of digital payments in our treatment group.

Appendix C: Analysis on unmatched samples

In this section, we take our main specification in the paper and produce estimates using unmatched samples. Table C.1 contains the final estimates with unmatched samples. The estimates are consistent with those in our main analysis. Tables C.2 to C.5 contain additional estimates for unmatched samples corresponding to those in the paper using matched samples. We find that the estimates are generally stable with respect to our matching procedure.

Table C.1 Main results, unmatched samples

VARIABLES	(1) Basket size	(2) Basket size	(3) Return rate	(4) Return rate	(5) No. of Trans.	(6) No. of Trans.
after	-312.4***		0.000926		-1,263	
	(2.448)		(0.000566)		(1,192)	
treated	174.5***		-0.00302		-15,205***	-13,983***
	(14.44)		(0.00240)		(1,329)	(1,342)
after_treated	41.72**	75.49***	-0.0497***	-0.0495***	1,084	-138.3
	(17.39)	(16.96)	(0.00349)	(0.00406)	(1,750)	(1,726)
Constant	1,672***	1,580***	0.231***	0.232***	15,683***	14,436***
	(2.001)	(0.369)	(0.000387)	(5.44e-05)	(879.9)	(596.5)
Customer and Date FE	NO	YES	NO	YES	NO	YES
Observations	1,379,536	673,194	2,286,025	1,826,890	171	162
R-squared	0.015	0.545	0.000	0.275	0.633	0.822

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.2 Auxiliary regressions, unmatched samples

VARIABLES	(1) No. of items	(2) No. of items	(3) Item price	(4) Item price
$Demo_d$	-0.354***		10.13***	
	(0.00199)		(1.082)	
$Switcher_i$	0.219***		-11.23**	
	(0.00940)		(4.605)	
$Demo_d \times Switcher_i$	-0.0177	0.0669***	33.95***	16.51***
	(0.0134)	(0.0144)	(6.954)	(5.976)
Constant	1.842***	1.752***	907.9***	843.9***
	(0.00144)	(0.00140)	(0.741)	(0.447)
Customer FE	NO	YES	NO	YES
Date FE	NO	YES	NO	YES
Observations	1,387,652	680,271	2,286,025	1,826,890
R-squared	0.024	0.504	0.000	0.529

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.3 Ignoring time series information, unmatched samples

VARIABLES	(1) Basket size	(2) Basket size	(3) Return rate	(4) Return rate
$Demo_d$	-291.3***	-343.2***	0.000414	0.000977
	(3.081)	(3.716)	(0.000510)	(0.000985)
$Switcher_i$	102.6***		0.0109***	
	(18.94)		(0.00316)	
$Demo_d \times Switcher_i$	17.65	69.55***	-0.0535***	-0.0541***
	(26.78)	(15.37)	(0.00446)	(0.00410)
Constant	1,709***	1,831***	0.216***	0.215***
	(2.222)	(2.549)	(0.000368)	(0.000676)
Customer FE	NO	YES	NO	YES
Observations	1,675,025	378,460	1,675,025	378,460
R-squared	0.005	0.918	0.000	0.501

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.4 Heterogeneous effects, unmatched samples grouped by pre-treatment average basket size

	Basket size			Return rate		
VARIABLES	Low	Mid	High	Low	Mid	High
$Demo_d$	312.5***	125.4***	-530.7***	-0.00345	-0.00448*	-0.00782***
	(3.119)	(3.533)	(6.657)	(0.00230)	(0.00233)	(0.00262)
$Demo_d \times Switcher_i$	83.16***	38.34***	50.74**	-0.0572***	-0.0439***	-0.0427***
	(10.16)	(11.37)	(20.64)	(0.00751)	(0.00751)	(0.00813)
Constant	475.6***	802.8***	1,749***	0.231***	0.231***	0.233***
	(2.099)	(2.375)	(4.455)	(0.00155)	(0.00157)	(0.00176)
Customer FE	YES	YES	YES	YES	YES	YES
Observations	74,166	74,166	74,164	74,166	74,166	74,164
R-squared	0.576	0.524	0.621	0.500	0.501	0.498

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Table C.5 Heterogeneous effects, unmatched samples grouped by pre-treatment average return rate

	Basket size			Return rate		
VARIABLES	Low	Mid	High	Low	Mid	High
$Demo_d$	-92.39***	109.5***	-24.47***	0.227***	-0.0225***	-0.451***
	(6.240)	(6.449)	(8.017)	(0.00204)	(0.00283)	(0.00350)
$Demo_d \times Switcher_i$	39.79*	65.50***	47.31*	-0.0499***	-0.0616***	-0.0634***
	(21.36)	(25.13)	(28.11)	(0.00617)	(0.00979)	(0.0109)
Constant	1,095***	806.5***	1,012***	-0	0.251***	0.678***
	(2.991)	(3.126)	(3.850)	(0.000961)	(0.00136)	(0.00166)
Customer FE	YES	YES	YES	YES	YES	YES
Observations	115,288	49,442	57,766	115,288	49,442	57,766
R-squared	0.624	0.663	0.631	0.594	0.503	0.698

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Appendix D: OLS with interaction approach

In this appendix, we present an alternative approach to measuring our effects of interest. Rather than measuring differences between switchers and non-switchers, we estimate a simple regression containing covariates for payment method, post-demonetization period dummies, and the interaction between the two. Our estimates in Table D.1 are consistent with our main results.

With respect to basket size (columns 1 and 2), we see that, controlling for time and customer fixed effects, orders made using digital payments are generally smaller. However, this pattern reverses after the demonetization—suggesting that an exogenous shock affecting the adoption of digital payments has a positive effect on basket size. Meanwhile, the return rate (columns 3 and 4) is negatively associated with choosing digital payments, and this relationship is unaffected by the exogenous shock.

Table D.1 OLS with interaction

VARIABLES	(1) Basket size	(2) Basket size	(3) Return rate	(4) Return rate
$Digital_i$	208.4***	-111.9***	-0.0496***	-0.0497***
	(13.72)	(22.16)	(0.000565)	(0.00117)
$Demo_t$	-339.2***		0.000812*	
	(10.69)		(0.000484)	
$Digital_i \times Demo_t$	108.3***	158.9***	-0.000396	0.000777
	(18.56)	(26.18)	(0.000799)	(0.00136)
Time and Customer FE	NO	YES	NO	YES
Constant	1,734***	1,742***	0.231***	0.231***
	(7.765)	(7.654)	(0.000332)	(0.000411)
Observations	2,522,869	1,543,530	4,528,324	3,914,820
R-squared	0.001	0.710	0.003	0.227

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

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