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Do households care about cash? Exploring the heterogeneous effects of India's demonetization*

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Abstract

The recent demonetization exercise in India is a unique monetary experiment that made 86 percent of the total currency in circulation invalid. In a country where currency in circulation constitutes 12 percent of GDP, the policy turned out to be a purely exogenous macroeconomic shock that affected all agents of the economy. This paper documents the impact of this macroeconomic shock on one such systematically important agent of the economy: the household. By construction, the policy helped households with bank accounts in disposing of the demonetized cash. We use a new household-level data set to tease out the effects of this policy on households with no bank accounts relative to households with bank accounts. Our results show that the impact of demonetization on household income and expenditure has been transient with the major impact being seen in December-2016. We find that households with no bank accounts experienced a significant decrease in both income and expenditure in December-2016. There is significant heterogeneity in the impact across households in different asset classes. We also show evidence of recovery of household finances whereby households were able to smooth out consumption during the post-demonetization period. However, this recovery phase is associated with an increase in household borrowing from different sources, primarily for the purpose of consumption. In particular, informal borrowing (money lenders, shops) increased substantially during this period. Thus, the policy although transient in nature, contributed to the unintended consequence of increased leverage for households.

JEL Codes: E21, E51, G28

Keywords: Demonetization, Household finance, Leverage

*The views and opinions expressed in this paper are those of the authors and do not necessarily represent the views of the Reserve bank of India, Bank of England or any other institution that the authors may be affiliated with.

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1 Introduction

On November 08, 2016 the Prime Minister of India, Narendra Modi, announced that higher denomination notes (500 and 1000 rupee notes) will cease to be legal tenders from the midnight of the same day. The demonetized notes comprised 86 percent of the total currency in circulation. The demonetization shock can be characterized as an exogenous macro-level shock impacting macro fundamentals, but its effects were expected to percolate to the micro level since cash plays an essential role in the day to day transaction of the Indian economy.[1] Moreover, the informal sector in India is large contributing 43.2 percent to the Gross Value Added and employing more than 80 percent of total labor force.[2] Given the large size of the informal sector, a cash shortage due to demonetization is expected to impact the majority of the players in the Indian economy. In this paper we focus on one such important player in the economy: the households. We look at household level data to tease out the effects of this sudden liquidity shock on income and expenditure. We then delve deeper to ask if demonetization had a heterogeneous effect on households. Although, the costs of demonetization appear almost immediately while the benefits are expected to be seen in a more medium term horizon with the broadening of the tax base and more digitization of payments, in this paper, we mainly focus on the short term costs of demonetization, given that the available time series for analyzing the benefits is short. However, we provide some evidence of the recovery phase that followed after demonetization. In what follows, we try to quantify the impact of the policy on households, and also uncover potentially interesting and important dimensions of heterogeneity in the data. Before we provide more details of the policy in the the next section, we present a brief review of the literature to situate our study in the larger context of liquidity constraints.

[1]Currency in circulation as a percentage of GDP is 12 percent as of March, 2016 and 11 percent as of March, 2018. The numbers are calculated using official numbers released by the Reserve Bank of India and Central Statistics Office.

[2]CSO [2018]and ILO [2018]

Our paper relates to the literature on household liquidity, income shocks and consumption smoothing. Several empirical studies on household saving and consumption examine the importance of liquidity constraints (Zeldes [1989];Jappelli [1990]; Runkle [1991]; Jappelli et al. [1998]) and quite a few of these papers use data on credit card usage and change in borrowing limits. Zeldes [1989] partitions households in his sample according to financial wealth relative to income and total wealth relative to income and defines a constrained household as one with assets worth less than 2 months of income. Souleles [1999] identifies credit constrained households by holdings of liquid wealth relative to earnings. This classification of households allows him to document that the consumption of non-durable goods for credit constrained families (the bottom 15% of the liquid wealth-to-earnings distribution) is sensitive to predictable changes in earnings, whereas non-durable consumption for unconstrained households (the top 25th percentile of the liquid wealth-to-earnings distribution) is not sensitive to these anticipated changes. Gross and Souleles [2002] examine households' responses to exogenous changes in the borrowing limit on credit cards. They find that, on average, consumers increase their debt holdings by 10% to 14% of the increase in the borrowing. Investigating the effects of the US Supreme Court decision that deregulated bank credit card interest rates in December 1978, Zinman [2003] compares consumers' acquisition and usage of credit cards between states that mandated binding usury limits before the court decision and states that were unaffected by deregulation. His results suggest that households who seem to be credit constrained used the easier access to credit to acquire credit cards and borrow frequently on their new credit cards. More recently Krueger and Perri [2011] show the effects of labor income shocks, on consumption, are modestly persistent. This is so because the consumption can be well insured using simple unsecured borrowing and saving.

Our definition of being liquidity constrained is different from the above literature because India is relatively more cash-based than other advanced economies. The demonetization exercise reduced the amount of cash that individuals held, and we seek to explore the adjustment process that followed thereafter. Given the nature of the exercise, having a bank account was quite essential because it was easier to exchange the demonetized banknotes. We compare the households with bank accounts with those that did not have access to bank accounts. In addition, we look at the impact on households along the entire asset distribution. To this end, we construct an asset index and look at the impact of the liquidity shock on various quartiles of this distribution.

There is an emerging strand of literature that specifically studies the demonetization exercise in India. Aggarwal and Narayanan [2017] study the impact on the agricultural sector while Dash et al. [2017] show how demonetization has led to households savings through more formal channels. RBI [2017] analyzes the broad macroeconomic trends in the aftermath of demonetization and Behera et al. [2017] study the impact on the financial sector. Our study, in contrast, uses micro-data at the household level, and analyzes the unintended heterogeneous consequences on the households. We confirm the results obtained in previous studies that the aggregate macro impact was transient. In contrast to other studies, however, we document the impact of the macro-level demonetization shock at the micro level. Our results show that the impact of demonetization on household income and expenditure has been transient with the major impact being seen in December-2016. We find that households with no bank accounts experienced a significant decrease in both income and expenditure in December-2016. These effects however differ for households across different asset classes and across professions. We also show evidence of recovery of household finances whereby households were able to smooth out consumption during the post-demonetization period. This recovery phase is associated with an increase in household borrowing from different sources, primarily for the purpose of consumption. In particular, informal borrowing (money lenders, shops) increased substantially during this period. Our results thus show that the policy although transient in nature, contributed to the unintended consequence of increased leverage for households, thereby leaving them more vulnerable than before.

The rest of the paper is organized as follows. Section 2 presents the background and some details on demonetization. Section 3 presents the data and descriptive statistics. We also discuss some due-diligence we have done on the data set we have used in this paper. Section 4 discusses the empirical strategy that we have used in this paper. Section 5 presents the results and section 6 concludes.

2 Demonetization: Background and discussion

The objective of demonetization as was claimed initially, was to target black money and eventually curbing corruption. One other objective that was highlighted during the initial phases was to flush out the fake currency notes that have been a concern for both the Government and the Reserve of India (RBI) for a long time. But the amount of fake currency in the total system, or at least what is identified as fake currency is very low. As per RBI Annual Report 2016-17, 0.003 % of the total notes supplied in 2016-17 were identified as Fake Indian Currency Notes (FICN). But, as of 2016-17 the 500 (old design) and 1000 rupee notes accounted for 75 percent of the total FICN detected by the banking system. Since the use of FICN are mainly through higher denomination notes, it was believed that the move would discourage the use of fake currency in the system.

Whatever may be the objectives of demonetization, removing 86 per cent of the currency in circulation in order to meet those objectives is bound to have short and medium term implications on the economy. The immediate monetary phenomenon is well captured in figure 1 below, where it can be seen that the currency in circulation went down drastically in the month of November-2016 and Dec-2016. As remonetization commenced after the initial few weeks of hardship, the currency in circulation, in the recent months has slowly reverted back to a level comparable to the pre-demonetization level. Currency that is with the public and is considered to be part of the money supply also seems to revert to the similar levels in the recent months as in the pre-demonetization period, after the shock in November-2016.

The announcement was made late in the evening of November 08, 2016. The timing of the announcement was probably deliberate in order to minimize panic among people, and gave time to people to absorb the information. However, needless to say, the announcement was a pure surprise. The information was not leaked prior to the announcements from any person in the government or the Reserve Bank of India. The fact that even internal officials did not have an iota of such a decision, gives a sense of the kind of secrecy that was maintained prior to the announcement.

As the announcement was made late in the evening, there was no chaos reported that night. Reports started coming from the next morning. As was the direction, for the initial few days, general public were allowed to exchange the old 500 and 1000 rupee notes in any bank and branch. Specifically, a person having old notes had two avenues to dispose them off: (1) to exchange the old notes in exchange of new notes or (2) to deposit the old notes in to their deposit accounts. The first way of disposing away the old notes were restricted to only Rs. 4000 per person per day. Initially, people were trying to go by the first avenue to dispose the old notes, even though there were restrictions on the amount they could exchange. The banks also started exchanging the old notes from the general public regardless whether they held an account with them. But the huge volume of such transactions was hard for the banks to handle. The smaller bank branches found it difficult to handle the volume of people and the volume of transactions. The difficulty stemmed from the fact that new notes were not arriving at a rate that could match the demand from people. At one point when the banks were not able to match up the pace of exchange, they reportedly were not encouraging exchange of old notes from non-account holders. Although there were restrictions that were put on the amount of transactions per day per person by the RBI, there was no restriction as such to restrict the banks to their customers. This was as an operational move and no direction was given by the RBI in this regard. However, even after putting these restrictions, the banks found it hard to manage with the volume of its own account holders.

The second channel of disposing off the old notes was to deposit them in to the deposit accounts. The effect of this direction was a spike in the cash holdings of the Banks. In fact, the cash on hand with banks (see Figure 2) increased by 288 per cent between

October-16 and November-16. As the process of remonetization normalized from the month of Jan-2017, the cash holdings of the banks came down, and remained stable in the recent months. The decrease in cash holdings in the month of Jan-17 can be attributed to the withdrawing of equivalent amount of cash in new denomination by the public as was deposited during demonetization.[3] Now, the financially excluded people could not exploit the bank channel of depositing old notes as this was only restricted to the account holders. All scheduled commercial banks and urban cooperative banks were tasked to accept deposit in old currencies. However, the District Central Cooperative Banks (DCCB) were barred from accepting deposits in old notes. Since DCCBs are attached to Primary Agricultural Credit Societies, this move may have hit the farmers and people in the rural areas who dependent on agriculture. The objective of such a ban on transactions by DCCBs was to minimize the fraudulent transactions that were reported from some DCCBs. There were some restrictions on deposits in to individual bank accounts as well. Since the restrictions and limits kept on being revised during this period, the last revision of such a restriction quoted that deposits more than 2.5 lakhs would attract some penalties. Although it is expected that people who have bank accounts would have preferred this channel of disposing off their cash, but cash shortage in banks was a widespread phenomenon. Thus regardless of which way people resorted to dispose of the cash, people had to face the hardship of getting new notes to carry on their transactions. The first few days' of panic was due to the process of depositing the old notes. The identification and checks by banks on the depositors and their accounts, and more checks in case of non-account holders made the process cumbersome.

During the first few days, the government gave some respite to the people by allowing them to use the old currency to pay for public utilities like paying electricity bills and highway tolls. The Government repeatedly extended the deadline for these exemptions which ended on December 15, 2016. In fact, highway tolls were waived off until December 02, 2016. Fuel stations were also allowed to take accept old currencies until December 02, 2016. In the rural

[3] This may also be on account of the liquidity operations by the RBI as it took special measures during demonetization to mop up the excess liquidity in the system.

sector, farmers were given relief by allowing them to use old currency notes to buy seeds. This scheme was announced by the government on November 21, 2016 for purchase of seeds for central and state government outlets and Agricultural Universities. As the process of remonetization took pace, the RBI kept relaxing the withdrawals restrictions for the banks.

3 Data

The Consumer Pyramids (CP) database is a survey based data on households. The database covers around 160,000 households during each wave of the survey. Each household in the database is surveyed every 4 months and a block of four months is called a wave. In each of the months in a particular wave, one-fourth of the sample is surveyed. During the survey, the households are asked to provide data for the preceding four months. The database is divided in to seven modules, each of which covers a different set of survey questions. Among these seven modules, four modules cover data on stock variables. These include questions regarding household characteristics, assets and liabilities, consumer sentiments and unemployment status. Data pertaining to these modules appear every four months in the data set. The dynamic variables pertaining to income, consumption, and their sub-components are covered in three different modules. Unlike the modules that cover static variables, data for these modules are available for every month.

The survey is primarily done at the household level that covers individual members as well. For example, demographic characteristics, unemployment status, and income composition are available for individual members of the households. However, expenditure details and asset and liabilities positions are available only at the household level. Since, in this paper, we are mainly looking at income and consumption across different asset quartiles, we restrict the unit of observation to the household. We use the demographic characteristics of the head of the household (HOH) whenever we need to dis-aggregate the data in those dimensions or use them as control variables. The final data set we use comprises of approximately 100,000 households over the period January-2015 to November-2017. To maintain consistency we have tried to work on a balanced sample. The dropping of observations while ensuring a balanced sample is mainly due the movement of families or change of family structure, and not due to any sample selection issues.

One important distinction of this data set when compared to other available household level databases is the panel structure. In this data set, information on household income and expenditure, asset holdings are available over a period of time. The panel structure of the data is essential for our analysis because we want to capture the change in household income and consumption pattern before and after the policy which cannot be executed using a cross section data. There have been a couple of studies that looked at the effects of demonetization at the dis-aggregated level. Since the policy was implemented at a particular point of time, one needs information on both the pre and post policy periods on a homogeneous group of individual units. In order to exploit the panel structure, most of the earlier studies have based their analyses at the district-level/ national where it is possible to create a high-frequency panel data covering both pre and post policy period. This paper is the first of its kind to use a panel data set on households to answer some basic questions with respect to demonetization.

Since the CP is a new data set, we try to do some due diligence to establish the credibility of the data. In India, the National Sample Survey Office (NSSO) conducts household surveys. Their consumption expenditure survey is done annually where they cover around 100,000 households. The coverage of the data set is huge and they cover a lot of details on household characteristics and consumption. NSSO does an Employment-Unemployment survey where information related to employment characteristics, wages and benefits are recorded. This survey is done every five years. A decadal survey on assets and liabilities is also done by NSSO that covers details on debt and asset holdings of households. In order to check consistency of the CP data set, we present some comparable variables from both CP and NSSO. Table 1 below presents the share of expenditure in total monthly expenditure on different heads.

The numbers are arrived at by applying the relevant weights from both the data sets. We see that the CP data produces reasonable estimates for the shares of food and non-food expenditures in total expenditure when compared to the NSSO. However, if we assume that spending pattern of households have remained unchanged between 2011-12 (NSSO data) and 2014-17 (CP data), CP seems to overestimate the share of food and underestimate the share of non-food expenditure for both rural and urban households.

Table 2 presents some state-wise aggregates in levels of total expenditure and share of food and cereals in total expenditure. The third column reports the difference between monthly per capita expenditure (MPCE) between NSSO and CP estimates. It turns out that CP underestimates the MPCE across all states. However, the shares of food and cereals in total expenditure estimated from the two data sets seem to be consistent across all states.

Figure 3 presents the correlation between District GDP obtained from Indicus and total income estimated from CP. This cross section scatter plot reveals a positive and significant correlation between the two data sets. In other words, districts that have higher GDP also report higher income as estimated from CP database.

The comparisons drawn with other independent data sources give some evidence on the credibility of the data. Although, the rural/ urban shares of expenditure from CP seem to be off from NSSO, this could be due the fact that CP over-samples the urban households. The difference between the levels of expenditure between NSS and CP may be attributed to the inclusion of imputed rent in NSS data which is not included in CP data. Also, since NSS data is collected at a certain point of time, it may include some long term expenditures incurred during the year. The CP data, being a panel data set may smooth out such expenditures across different months. In summary, we think that CP data covers a fairly representative sample of households. The panel structure of households is a unique feature of the data which is not found any similar data sets that are available. The data set also appears to be of reasonable quality and suits the purpose of our analyses.

3.1 Descriptive Statistics

The basic unit of observation in the CP data set is the household. Since we focus our analysis on the household with and without bank accounts, we present summary results with respect to these two categories of households. Table 3 reports the monthly income and expenditure for the treatment and control groups.[4] Of the entire sample of households, only 17 percent of the households do not have any bank account. This number is less than the 31.2 percent reported in NSSO [2013] report because our estimate includes only those households who report no bank accounts for any member in the household. We identify households with bank account if at least one member has one bank account including the head of the household. We use this restrictive criterion because during demonetization, households could channelize their cash holdings of demonetized notes through any member in the household who have a bank account. So, we expect that the effect of demonetization would be highest for the households who have no bank accounts including the head of the household. On average, total income and wages are lower for households with no bank accounts while average expenditure is slightly higher for these households compared to households with bank account. We think that households who save less choose not to open a bank account. Although there was an increase in bank accounts post-demonetization, we restrict our measure of bank accounts during the pre-demonetization period. Since demonetization was an unexpected shock, restricting ourselves to this identification strategy allows us to separate out any endogenous effect of demonetization emanating from households who chose to open bank accounts post-demonetization.

3.2 Construction of asset index

The objective of this study is to tease out the heterogeneous impact of demonetization on households. We think asset holdings is an important dimension to exploit in the the Indian economy. Asset holdings can be of two types: physical asset holding and financial asset

[4]The time series trends for income and consumption are presented in the Appendix.

holding. Physical assets would include television sets, refrigerator, washing machine, air-conditioner, house, cattle etc. Financial assets include fixed deposits, mutual funds etc. In India, there is predominance of physical asset holdings than financial asset holdings which have relatively lesser penetration into Indian household finance setup. Thus, for our purpose in this paper, we mainly focus on physical asset holdings rather than financial asset holding to classify households into different asset quartiles. Also, data on financial assets in the CP data set is recorded in a categorical sense i.e whether or not the household own a particular asset or not, while on the other hand CP records the actual quantity of a physical asset by the the households. However, at a later stage we show that there is a positive relationship between physical assets and financial assets which warrants the use of any one of the asset definitions in our study.

We face two challenges while using the assets and liabilities information in the CP data. First, the data is recorded as number of units and no monetary value is attached to the assets. So, we cannot simply add the assets to come up with an asset index for the households. Second, the weight of each asset differs in the basket of physical assets. For example, a house and refrigerator must have different weights in the basket. We overcome these two problems and come up with the following methodology to arrive at an index value of physical assets for households. Let $X_{i,j,t}$ be number of units of asset j held by household i at time t. Let $\mathbf{1.}\boldsymbol{X_{i,j,t}}$ be the indicator variable if the household owns at least one unit of asset j. We have:

$$\begin{cases} \mathbf{1.}X_{i,j,t} = 1 & if\, i\, owns\, j\, at\, t \\ \qquad\quad = 0 & otherwise \end{cases} \tag{1}$$

The relative importance of asset j is given by:

$$W_{jt} = [1/(\sum_{i=1}^{N} \mathbf{1.}X_{ijt}/N)] * w_{it}\, , \forall j \epsilon [1, J]\, , \forall t \epsilon [1, T] \tag{2}$$

where w_{it} is the sample weight of the household which is essentially the reciprocal of probability of sampling the household from the population. Using this relative importance of each asset we can compute the asset index for each household, which is given by:

$$\sum_{j=1}^{J}[X_{ijt}] * W_{jt}\,,\,\forall i\epsilon[1,N]\,,\forall t\epsilon[1,T] \tag{3}$$

For the purpose of this paper, we compute this asset index for each household for each wave. However, since we are dividing the households in to quartiles of the asset index, we use the asset distribution for the pre-demonetization period. Ideally, we do not want to allow for households to switch between asset quartiles, although we do not see this happening in the data often. In other words, if demonetization had changed the distribution of assets across households we could not have used it to identify the households in to different asset classes.

Table 5 reports the asset index computed across waves. We see that the distribution did not move because of demonetization. Thus, we can safely use this distribution to identify the households into separate asset quartiles. When reporting results based on the asset quartiles we have restricted ourselves to the asset index attached to each household at the pre-demonetization period, even though we do not find any significant change of this asset index across different waves. Table 4 reports this asset index for the treatment and control groups. The asset index for households with bank accounts is systematically higher than the households with no bank account. The distribution of this asset index for the treatment group also lies to the left of that for the control group. So, on average the treatment group holds less assets than the control group in the pre-demonetization period.

4 Empirical Strategy

In this section we discuss the empirical strategies we use. First, we discuss our baseline specification and two variants of the baseline specification we use to tease out the heterogeneous effects of demonetization on households. Second, we discuss the specification we use to document the the increase in household indebtedness.

4.1 Baseline Specification

One of the officially announced objective of demonetization was to curb the flow of black money. In order to meet this objective, the directions during the early stages were in favor of those with bank accounts. As mentioned earlier, general public were allowed to exchange notes in any bank. However, many banks due to logistical difficulties, restricted these facilities to account holders only. On the other hand, the government allowed transactions in old notes for certain public services like tolls, gas stations, hospitals etc. So, there were mainly three avenues to dispose of the old notes: either deposit them in the bank accounts, exchange them with new notes or spend them on public utilities. Clearly, the policy was favorable to individuals who had a bank account where in they had an option to deposit the old notes in their accounts. Our unit of observation is the household. Within a household there could be members with and without bank accounts. Since a household may dispose of the old notes even if one member has a bank account, we would like to identify those households in which no member holds a bank account. This is our pure treatment group. Since the policy was implemented on November 08, 2016, we consider the month of November and post-November as the post-policy period. Our baseline specification looks like the following:

$$y_{it} = \beta * (Post * Treatment) + \gamma_t + \theta_i + \epsilon_{it} \tag{4}$$

where y_{it} is the dependent variable of interest in log terms. The set of dependent variables include total monthly income, total monthly expenditure and their sub-categories. The dummy variable *Post* takes the value 1 for months of November-2016 to February-2016. We restrict our baseline specification to the month of February-2016 to focus on the immediate effects of demonetization.[5] The dummy variable $Treatment$ takes the value 1 for households with no bank accounts. We classify the households with at least one bank account as the control group. In this sense, we are restrictive in identifying our control group, and want to take into account the fact that households may use the bank account of any member within the household to dispose the old notes. We saturate our specification with household fixed effects (θ_i) that control for any time invarying household characteristics, regional characteristics and demographics. We also include month fixed effects (γ_t) that control for any seasonality during the specified months. The main coefficient of interest is β that gives us the relative effect of demonetization on households without bank accounts compared to households with bank accounts.

We use two variants of our baseline model. First, we want to explore the heterogeneity across households. We classify the households into four asset quartiles based on the asset index we computed. We then estimate equation 4 for four different asset quartiles: from low to high:

$$y_{iat} = \beta_a * (Post * Treatment) + \gamma_t + \theta_{ia} + \epsilon_{iat}\,, \exists\, a\, \epsilon\, [1, 4] \tag{5}$$

where a is the asset quartile of the household. We hypothesize that households with higher value of assets would be less hurt due to demonetization than households with lower value of assets. Since physical assets are less liquid than financial assets, one may argue that the latter is a better way to classify households. But there is a positive correlation between the asset indices constructed using financial assets and physical assets. We prefer to use the physical assets because it gives us a continuous distribution while financial assets give us information only on the extensive margin.

Second, our baseline specification, does not allow us to identify the immediate effect of demonetization and the recovery after that. In order to tease the immediate effect, we use

[5] In fact, there were other confounding macroeconomic shocks during the post demonetization period like the introduction of GST (July-2017) etc. that may conflate with the medium-term effects of demonetization.

the baseline specification augmenting by the monthly interaction terms. We use the following specification:

$$y_{iat} = \sum_{t=-2}^{+6} \beta_{at} * (Treatment * Month_t) + \gamma_t + \theta_{ia} + \epsilon_{iat}\,, \exists\, a\, \epsilon\, [1,4] \tag{6}$$

where the coefficients β_{at} give us the month-wise effect of demonetization 2 months before and 6 months after demonetization.

4.2 Borrowings: Logit specification

Since demonetization shock was similar to a liquidity shock to the household balance sheet, we would like to investigate whether there has been any change in household indebtedness. Specifically, if households smooth out consumption during the period of the liquidity shock, we expect to see an increase in borrowings for the households. These borrowings could be from many sources: banks, money lenders, shops etc. Anecdotal evidence suggests that many households mitigated the shock by buying goods on credit from local shops. In the data, we do not see the amount of credit outstanding for the households. We only observe the categorical variable whether they hold any outstanding credit or not. To be clear, the data does not allow us to estimate the effect of the liquidity shock on household credit at the intensive margin. We can only estimate the effects on credit at the extensive margin. We use a simple logit specification with household fixed effects to estimate the increase in the likelihood of indebtedness due to the liquidity shock. We estimate:

$$(Pr\, b_{iat} = 1|\boldsymbol{X}) = \beta_a * (Post * Treatment) + \gamma_t + \theta_{ia} + \epsilon_{iat}\,, \exists\, a\, \epsilon\, [1,4] \tag{7}$$

where b_{iat} takes the value 1 if the households i, in asset class a, at time period t reports borrowing from a particular source. As with logistic regression, the error terms follow a logistic distribution. The rest of the terms carry the same meaning as in equation 4. The coefficient β_a caries a different interpretation. In this specification, β_a tells us the incremental increase in probability (log odds ratio) of borrowing after demonetization for households without bank accounts with respect to households with bank accounts.

5 Results

In this section we discuss the results. First, we discuss the results based on our baseline specification. Second, we tease out the time effects to see when the households got affected and when the recovery started. Lastly, we discuss the implications on household balance sheet due to the sudden liquidity shock.

5.1 Baseline Results

For Tables 6-15, we only report the coefficient of the interaction term (β) in equation 4 that captures the true effect of demonetization on the treatment group (households with no bank account) post demonetization relative to the control group (household with at least one bank account).

Table 6 reports the results for the baseline specification on income and the sub-components of income: wages, government transfers, and pensions. We see that, for the entire sample of households, there has been a slight increase in total income by about 1.5 percent post demonetization for the treatment group. Wages show a mild increase of 0.09 percent while other components of income do not show any significant increase. Tables 7-10 show the results on income for each asset class. If we look at asset classes 1 to asset class 3, we see that there is no statistically significant effect on income. However, asset class 4 shows an increase in income by about 3.2 percent. It is clear that, the increase in income we see in the total sample, mainly comes from the increase in income for the households in asset class 4. These could be due to the reporting of higher income by these households (in asset class 4) under the income declaration schemes for tax purposes announced by the government right around the same time as demonetization.[6] Moreover, since the shock was primarily a temporary liquidity shock, we do not expect to see a huge drop in income reported for households with a continuous flow of income. We would however show some evidence for different professions when we discuss the monthly effects.

Tables 11-15 report the results for expenditure and its components. Since demonetization was a liquidity shock, one would think the natural outcome to be a drop in expenditure. Table 11 reports the results for all households across all asset classes. As with income, we see that there has been an increase in expenditure by about 1.8 percent for the treatment group post demonetization. The increase has mainly come from an increase in spending on food and apparels. In fact the increase in spending on apparels increased by 3.3 percent which is more than the average increase in total spending. Breaking up in to asset classes (see Tables 12-15), we see that the increase in total spending was highest for the lower asset classes with total spending increasing by 2.1 percent. This increase is contributed by food and apparel with 2.6 and 13.2 percent increase respectively for the treatment group post demonetization. The increase in spending for the higher asset classes has been close to the average increase in spending for all asset class. It is counter-intuitive to see an increase in spending after a sudden liquidity shock. This could simply mean that households with no bank accounts wanted to get rid of the old notes by spending, as the bank channel to exchange and deposit old notes did not work for them. Moreover, it is important to note that the recovery phase post-demonetization has been quite rapid as the process of remonetization gathered pace. The months of Jan-16 and Feb-16 saw sharp recovery post demonetization which is essentially captured in these specification. A close look at the monthly effects would help us tease out, if any, an expected negative shock on income and expenditure.

[6]The Pradhan Mantri Garib Kalyan Yojana (PMGKY) was a voluntary income declaration scheme that came into effect on December 17, 2016 and continued until March 31, 2017. Under this scheme, people could declare undisclosed income only in the form of cash and bank deposits in Indian banks. The declaration attracted roughly 50 percent of the total amount in taxes and surcharges, and a mandatory deposit of 25 percent in the zero-interest Pradhan Mantri Garib Kalyan Deposit Scheme (PMGKDS) for four years. The proceeds from this scheme were intended to be spent toward poverty alleviation programs.

5.2 Monthly trends

As mentioned in the previous paragraph, the baseline specification cannot identify the immediate effect of demonetization, as it covers the recovery phase post demonetization. In other words, it gives us a macro overview of the impact of the shock which seems quite innocuous at this point. However, a deeper analysis is required to understand the phases of the shock transmission, which is what we do next. In order, to tease out this effect, we run the specification 6 with interaction terms for each month. We plot the monthly coefficients for each of the asset classes for the months September-2016 to April-2017.

Figure 4 reports the results for household income for each asset class. There is roughly a uniform pattern across households for the months preceding demonetization. All asset classes show an increase in income in September-2016, a decrease in October-2016. Households experienced a slight improvement in November-2016 compared to the previous month although they are statistically insignificant for most of the asset classes. The magnitudes of these effects differ across asset classes. The effects of demonetization can be seen in December-2016, when income decreased by more than 2 percent and 5 percent for households in the lowest and the highest classes respectively. We do see a decrease in income for the second and third asset quartiles, however, the coefficients are statistically insignificant. These effects slowly die down in the post-demonetization months, the sharpest recovery being seen for the 4th asset quartile.

Figure 5 reports the results for household expenditure for each asset class. For all asset classes, there were signs of increase in expenditure in the pre-demonetization period. Specifically, for the month of November-2016, when we see an increase in income, we see an increase in the expenditure as well. Before that, October-2016 was bad as all asset classes saw a decrease in expenditure. Post-demonetization, December-2016 saw a large drop in expenditure and this drop is significant for all asset classes. Expenditure for the treatment group decreased by about 7 percent for the highest asset quartile, while it decreased by around 3 percent for the 1st asset quartile. Post December-2016, all the asset classes saw a recovery in expenditure starting from January-2017.

The recovery phase post December-2016 is what is captured in the baseline specification which on average shows an increase in total spending post demonetization. However, when we break up the effect in to monthly effects, we see that the largest effect has been in the month of December-2016 and this is consistent across all asset classes. In terms of income, the largest negative impact is seen for the 4th asset quartile followed by the 1st asset quartile. We see the same pattern for expenditure well. The larger decrease in income and expenditure for the higher asset quartile could be because of the fact that these households are relatively more reliant on cash transactions. It would be interesting to see the effects of demonetization by profession and tease out the effects, if any, across the nature of the jobs.

5.3 Effects by profession

Figure 6 reports the coefficients for December-2016 for different professions. Panel A reports the coefficients for total income and Panel B reports the coefficients for total expenditure. We see that for income, the largest negative effect is seen for businessmen. While for expenditure, the coefficients are negative for almost all professions, and is seen in income, businessmen took the largest hit. Surprisingly, both for income and expenditure, white collar clerical employees and professionals report large negative effects. While we don't have a good explanation why this could be case, we can definitely say that the highest quartile mainly comprise of businessmen, and white collar employees which may be driving the large negative effect in that quartile compared to the lower quartiles.

5.4 Borrowings

We have shown that households across all asset classes experienced a drop in income and expenditure in the month of December-2016. However, there is significant heterogeneity in the magnitude of these effects. We also see a significant difference in the recovery phase for each of the 4 asset classes. In this section, we try to explain the mechanism that may have contributed to the recovery of the household finances after the sudden liquidity shock due to demonetization. Specifically, we focus on the borrowing channels that are available to the households with and without bank accounts how they have used these channels to smooth out their consumption levels post demonetization. It may be important to reiterate the nature of data on borrowings here. In the CP data, we only see the categorical variable on whether the households have borrowed from any source for any purpose. So, we are not able to quantify the amount of borrowings. We can only infer on the probability of borrowing for the households by using the binary responses of households on borrowings.

Figure 7 reports the fraction of households borrowing from any source for different purposes. The horizontal axis denotes the survey rounds for the treatment and control groups. Round 8 is the pre-demonetization period, while wave 9 includes the demonetization period. The post demonetization period starts from wave 10.[7] We see that on average, borrowings increased for households post-demonetization, and the increase has been primarily on account of consumption (maroon bars). Households without bank accounts appears to have borrowed more for consumption than households with bank accounts. This insinuates to the fact that households with no bank accounts are relatively more liquidity constrained than households with bank accounts, and they are likely to resort to borrowings to smooth out their consumption.

The source of borrowings however may be quite different from for the treatment and the control group. This distribution may also vary across the asset classes. Figure 8, reports the source of borrowings across the survey rounds for both the treatment and the control groups. As there has been an overall increase in borrowings, we see a secular increase in borrowings from banks, moneylenders and shops. The increase in borrowings from banks have increased significantly for the treatment group mainly because of the fact that many households may have opened bank account post-demonetization. Interestingly, the treatment

[7]Wave 8 covers the months of June-2016 to August-2016. Wave 9 covers the months September-2016 to December-2016. Wave 10 covers the months January-2017 to April-2017.

group in the fourth asset quartile has been proactive in approaching banks for borrowings than the lower asset quartile. The lower asset quartile on the other hand appears to be more comfortable with borrowings from money lenders as the fraction of households in that category (treatment and asset class1) increased significantly post demonetization. There is some similarity between the treatment group in asset class 1 and asset class 4 as far as borrowings from shops are concerned. Anecdotal evidence during demonetization suggests that households coped with the liquidity shock by buying goods and services on credit from shops. This seems to holds true for all the asset classes but the evidence is prominent for the households in the first and fourth asset quartiles.

Next, we present results from the logistic regressions as in equation 7. The coefficient tells us the relative increase in the probability (log odds ratio) of borrowing for the treatment group post demonetization. Figures 9 to 12 report the coefficient beta from equation 7 for each source of borrowing and for each asset class. It turns out that the probability of borrowing from any source increased more for the treatment group post-demonetization for asset class 3 compared to other asset classes. We now break these up in to different sources of borrowing. Figure 10 reports the coefficients for borrowing from banks. The treatment group in asset class 3 shows the highest increase in the probability of borrowing post demonetization. For borrowings from money-lenders (Figure 11), the treatment group in asset class 1 shows a significant increase in the probability of borrowing, while the treatment group is asset class 4 shows the least increase. This result is consistent with the observation that households in the lower asset quartile find it easier to approach a money lender. Borrowings from shops, as reported in Figure 12, increased for the treatment group in the 4th asset quartile. We see a negative coefficient for the 1st asset quartile which only means that relative to the control group, the probability of borrowings from shops for the treatment group decreased post-demonetization. This is mainly because of the fact, that within both the treatment and control groups, the fraction of households borrowing from shops increased post-demonetization (see Figure 8). But the increase has been more among households in the control group within the asset class.

Tying these results up with the baseline results we presented for income and consumption, it appears that the sudden liquidity shock had a temporary effect on the household finance. Households appear to smooth out their consumption and also recover from the temporary fall in consumption by resorting to borrowings. This mechanism seem to have increased the overall borrowings for households. Our logistic regressions show that the probability of borrowing from different sources, especially informal sources like money-lenders and shops increased post demonetization. The magnitude of such increases in the probability of borrowing however differs for different asset classes. Overall, our results show that households were able to tackle the sudden liquidity shock. However, there has been a structural shift of household indebtedness in the post demonetization period which may increase the stress on household finances in the medium term.

6 Conclusion

The recent demonetization exercise in India is a unique monetary experiment that made 86 percent of the total currency in circulation invalid. Using household level micro data, we document the heterogeneous effects of this monetary shock among the households that had access to bank accounts and those that did not (i.e. financially included vs. excluded households). We also, quantitatively evaluate the impact at various quartiles of the asset distribution.

We find that households with no bank accounts experienced a significant decrease in both income and expenditure in December-2016. The recovery in the post-demonetization period appears to be quick although, as we show in the paper, households managed to smooth consumption mainly by borrowing from informal sources such as money lenders and shops. This points to an important structural change that the Indian economy has undergone. The macro picture of the shock may look transient but it has contributed to increasing household indebtedness which in turn has made them more vulnerable than before.

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Tables

Table 1: Expenditure Shares: Consumer Pyramids and NSSO (All-India Averages)

	Rural		Urban	
Share in Total. Expen (%)	CP	NSSO	CP	NSSO
Cereals and Pulses	14.0	10.7	17.3	6.6
Milk and Milk products	10.1	8.0	9.4	7.0
Sugar	2.7	1.7	2.1	1.0
Edible Oil	5.0	3.7	4.0	2.7
Protein	6.8	4.8	6.4	3.7
Vegetables	7.3	6.6	6.1	4.6
Fruits	1.4	2.2	1.7	2.6
Total Food	**56.7**	**52.9**	**50.4**	**42.6**
Tobacco, Pan, Gutkha	2.7	3.2	1.9	1.6
Power and Fuel	15.4	8.0	18.6	6.7
Apparel	3.5	6.0	3.7	5.4
Footwear	0.9	1.0	0.9	1.0
Education	3.0	3.5	3.3	6.9
Health	1.8	2.2	1.9	2.0
Recreation	0.2	1.0	0.4	1.6
Toiletries	7.7	2.1	7.6	2.1
Transport	2.7	4.2	2.7	6.5
Total Non-Food	**43.3**	**47.1**	**49.6**	**57.4**

Notes: 'CP' is Consumer Pyramids. 'NSSO' stands for National Sample Survey Office.
Share of item 'x'=Monthly per capita Expenditure on 'x'/ Monthly per capita Total Expenditure .
Estimates from CP are based on monthly averages across states between the period Jan-2014 and July-2017.
The food and non-food sub categories may not add up. Comparisons are based on consistent sub-categories across the two data sets.
Estimates for NSSO are taken from "Key Indicators of Household Consumer Expenditure in India", NSS 68^{th} round. Period: July-2011 and June-2012.
All estimates are in 2011-12 Rupees.

Table 2: Comparison between Consumer Pyramids and NSSO

	MPCE			Share of Food in Total Expen. (%)		Share of Cereals in Total Expen. (%)	
	in Rs		Deviation (%)				
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
States	CP	NSSO	(2)-(1)/(2)	CP	NSSO	CP	NSSO
Jammu & Kashmir	1708.5	2132.5	19.9	48.5	54.4	9.8	10.1
Himachal Pradesh	2042.5	2641.9	22.7	46.0	47.2	12.5	7.1
Punjab	2390.2	2634.5	9.3	50.3	44.6	9.7	5.3
Chandigarh	3120.8	3051.9	-2.3	42.8	43.3	7.2	5.9
Uttarakhand	2151.0	2059.7	-4.4	49.9	50.3	11.8	8.9
Haryana	2255.5	2967.5	24.0	48.0	48.8	9.6	5.0
Delhi	1617.5	3106.0	47.9	49.1	43.1	11.6	5.4
Rajasthan	1529.5	2025.0	24.5	48.9	50.2	11.9	7.5
Uttar Pradesh	1442.3	1586.4	9.1	56.0	51.4	15.6	10.0
Bihar	1196.1	1336.3	10.5	61.7	58.0	22.0	14.5
Assam	1534.6	1684.1	8.9	52.0	58.0	16.0	14.1
West Bengal	1374.0	1900.0	27.7	57.9	54.6	17.2	13.4
Jharkhand	1230.0	1480.1	16.9	53.7	55.8	17.5	15.1
Odisha	1079.5	1445.4	25.3	53.4	54.5	17.5	14.7
Chhattisgarh	1129.3	1429.0	21.0	49.0	50.4	14.6	11.7
Madhya Pradesh	1231.5	1586.9	22.4	49.4	50.5	12.0	9.9
Gujarat	1471.2	2046.3	28.1	53.1	53.0	11.7	7.6
Maharashtra	1984.9	2357.0	15.8	49.4	50.0	13.2	8.1
Andhra Pradesh	1743.8	2224.7	21.6	51.1	49.7	18.3	9.3
Karnataka	1563.6	2251.7	30.6	47.5	48.7	13.9	8.5
Goa	2969.2	2782.9	-6.7	41.0	50.2	8.0	7.1
Kerala	2292.8	3095.8	25.9	44.8	42.2	11.4	5.3
Tamil Nadu	1708.5	2160.3	20.9	49.5	49.9	14.2	8.2
Puducherry	2055.9	2709.0	24.1	42.9	49.2	10.8	7.0
Total	1784.3	2195.6	18.5	49.8	53.6	15.6	9.2
Observations				24			

Notes: 'MPCE' is Monthly Per Capita Expenditure. 'CP' is Consumer Pyramids. 'NSSO' stands for National Sample Survey Office.
MPCE=Total Monthly Hhd. Expenditure/ Total Members in the Household.
Estimates from CP are based on monthly averages across states between the period Jan-2014 and Dec-2016.
Estimates for NSSO are taken from "Key Indicators of Household Consumer Expenditure in India", NSS 68^{th} round. Period: July-2011 and June-2012.
All estimates are in 2011-12 Rupees.

Table 3: Summary Statistics -Treatment and Control

	No Bank Ac		With Bank Ac	
	mean	sd	mean	sd
TOTAL_INCOME	11173.8	8162.9	12696.6	9054.9
WAGES	10128.3	7687.5	11223.6	8777.2
TOTAL_EXPENDITURE	7849.2	3764.8	7486.7	3218.6
EXPENSE_ON_FOOD	3597.4	1252.8	3791.2	1248.1
Observations	722,353		3,343,976	

Table 4: Asset Index, By Bank Account

Bank Account	mean	sd	p25	p50	p75	p90
No	16.2	20.6	4.3	7.5	18.0	46.1
Yes	18.2	21.3	4.9	10.4	22.0	49.0
Total	17.9	21.2	4.7	9.8	21.5	49.0

Table 5: Distribution of Asset Index

Statistic	**Wave 7**	**Wave 8**	**Wave 9**
Mean	17.67	17.44	17.06
Min	0	0	0
Max.	313.77	243.14	398.64
p10	2.18	2.22	2.20
p25	4.73	4.80	4.32
p50	9.24	8.59	8.33
p75	21.50	20.78	18.82
p90	48.0	48.94	48.16
Obs	132908	132399	132777

Table 6: Difference in Difference Estimation (Income: Over all asset classes)

	(1)	(2)	(3)	(4)
	Income	Wages	Govt Tranf	Pension
Post*Treatment	0.015***	0.009**	-0.005	0.013
	(0.003)	(0.003)	(0.006)	(0.010)
Month FE	Yes	Yes	Yes	Yes
N	689985	616719	90347	84752

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds with no bank Acs
and the post-demonetization months.

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 7: Difference in Difference Estimation (Income: Asset Class 1)

	(1) Income	(2) Wages	(3) Govt Tranf	(4) Pension
Post*Treatment	0.010	0.008	-0.046***	-0.007
	(0.005)	(0.005)	(0.011)	(0.022)
Month FE	Yes	Yes	Yes	Yes
N	144804	135713	17667	13973

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds with no bank Acs
and the post-demonetization months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 8: Difference in Difference Estimation (Income:Asset Class 2)

	(1) Income	(2) Wages	(3) Govt Tranf	(4) Pension
Post*Treatment	0.008	0.004	-0.026*	0.020
	(0.006)	(0.006)	(0.010)	(0.023)
Month FE	Yes	Yes	Yes	Yes
N	158768	147158	22439	16583

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds with no bank Acs
and the post-demonetization months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 9: Difference in Difference Estimation (Income:Asset Class 3)

	(1) Income	(2) Wages	(3) Govt Tranf	(4) Pension
Post*Treatment	0.007	0.009	0.039*	0.008
	(0.007)	(0.007)	(0.015)	(0.022)
Month FE	Yes	Yes	Yes	Yes
N	147123	133574	20496	15950

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds with no bank Acs
and the post-demonetization months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 10: Difference in Difference Estimation (Income:Asset Class 4)

	(1) Income	(2) Wages	(3) Govt Tranf	(4) Pension
Post*Treatment	0.032***	0.012	0.013	0.013
	(0.007)	(0.006)	(0.012)	(0.016)
Month FE	Yes	Yes	Yes	Yes
N	155078	125833	18060	27835

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds with no bank Acs
and the post-demonetization months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 11: Difference in Difference Estimation (Expenditure: Over all asset classes)

	(1) Expenditure	(2) Food	(3) Apparel	(4) Appliances	(5) Restaurants	(6) Transport	(7) Health
Post*Treatment	0.018***	0.019***	0.033**	0.006	0.011*	0.004	0.013*
	(0.002)	(0.002)	(0.012)	(0.009)	(0.005)	(0.005)	(0.006)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	689985	689985	510305	121677	411222	620468	628984

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds with no bank Acs
and the post-demonetization months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 12: Difference in Difference Estimation (Expenditure: Asset Class 1)

	(1) Expenditure	(2) Food	(3) Apparel	(4) Appliances	(5) Restaurants	(6) Transport	(7) Health
Post*Treatment	0.021***	0.026***	0.132***	0.014	-0.007	0.010	0.020
	(0.005)	(0.004)	(0.025)	(0.020)	(0.011)	(0.010)	(0.012)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	144804	144804	96327	18977	72998	132817	129632

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds with no bank Acs
and the post-demonetization months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 13: Difference in Difference Estimation (Expenditure::Asset Class 2)

	(1) Expenditure	(2) Food	(3) Apparel	(4) Appliances	(5) Restaurants	(6) Transport	(7) Health
Post*Treatment	0.014**	0.005	0.089***	0.037	0.025*	0.016	0.027*
	(0.005)	(0.004)	(0.025)	(0.022)	(0.011)	(0.011)	(0.011)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	158768	158768	112783	25247	89999	141829	142698

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds with no bank Acs
and the post-demonetization months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Table 14: Difference in Difference Estimation (Expenditure::Asset Class 3)

	(1) Expenditure	(2) Food	(3) Apparel	(4) Appliances	(5) Restaurants	(6) Transport	(7) Health
Post*Treatment	0.015**	0.013**	0.022	-0.030	0.011	0.017	0.029*
	(0.005)	(0.005)	(0.023)	(0.020)	(0.011)	(0.011)	(0.013)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	147123	147123	115084	27623	89287	130785	133830

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds with no bank Acs
and the post-demonetization months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

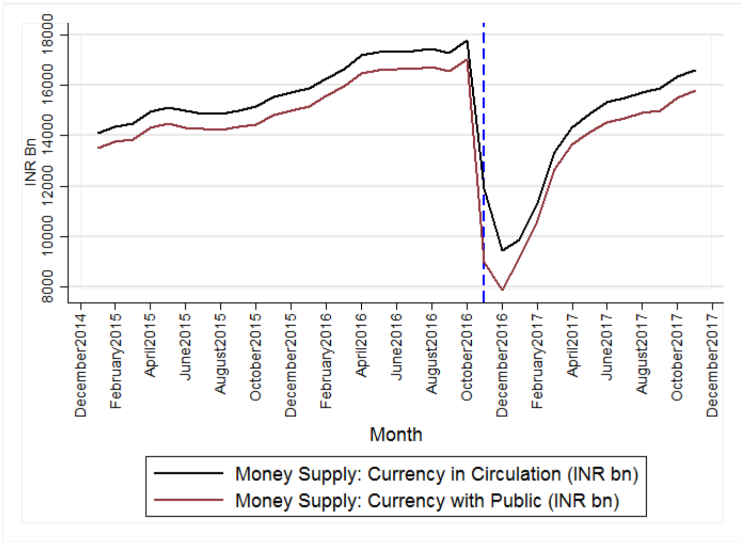
Table 15: Difference in Difference Estimation (Expenditure:Asset Class 4)

	(1) Expenditure	(2) Food	(3) Apparel	(4) Appliances	(5) Restaurants	(6) Transport	(7) Health
Post*Treatment	0.014**	0.024***	-0.096***	0.027	-0.000	-0.042***	-0.015
	(0.005)	(0.004)	(0.023)	(0.015)	(0.008)	(0.010)	(0.011)
Month FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes
N	155078	155078	122248	33008	109393	139321	145557

All specifications include Hhd FE. Standard errors are clustered at the Hhd level.
Post*Treatment denotes the interaction dummy for Hhds with no bank Acs
and the post-demonetization months.
* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

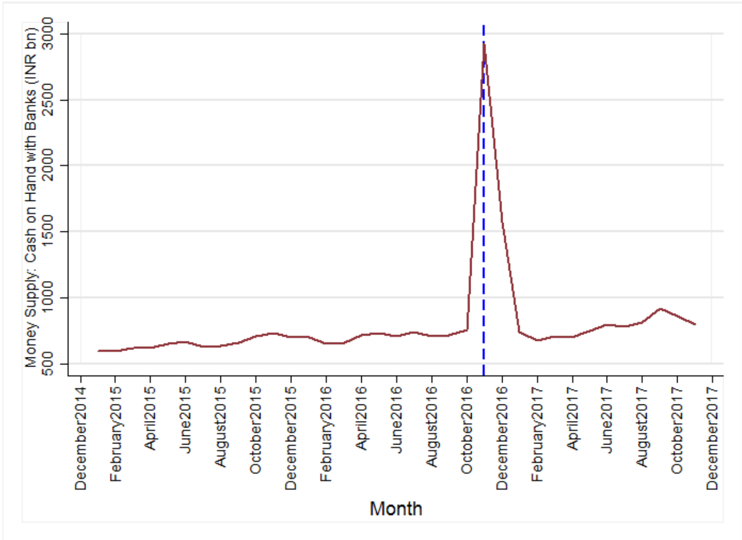
Figures

Figure 1: Currency in Circulation



Source: Reserve Bank of India.

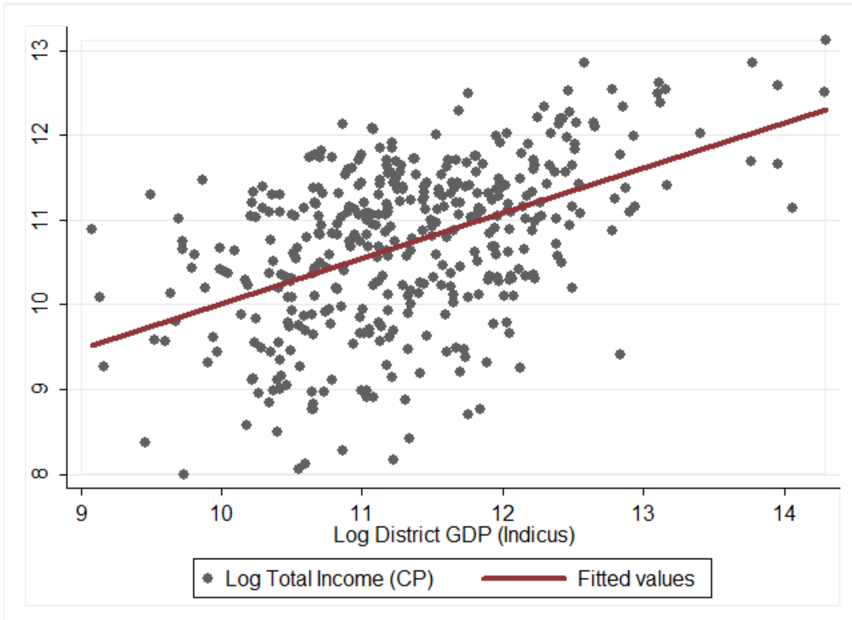
Figure 2: Cash on Hand with Banks

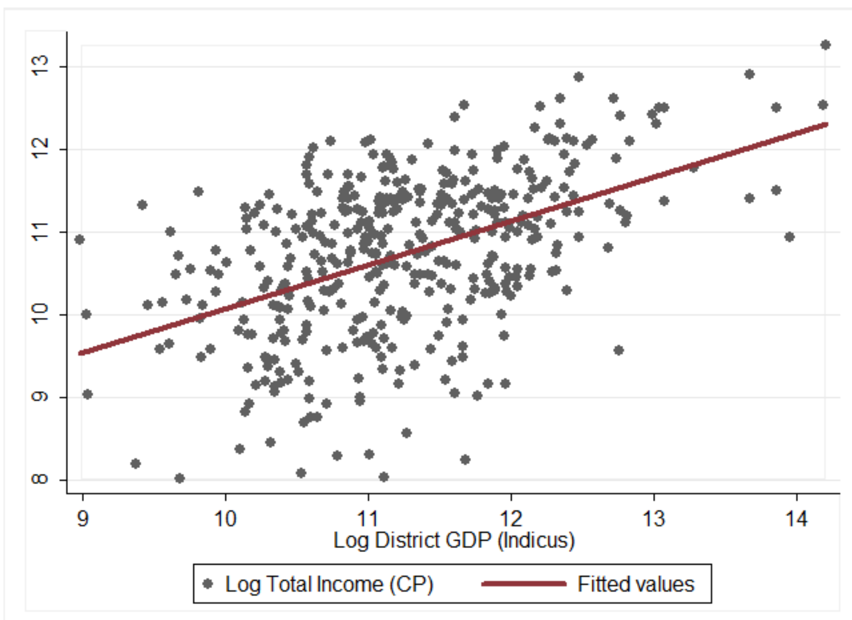


Source: Reserve Bank of India.

Figure 3: Comparing District GDP (Indicus) vs Total Income (Consumer Pyramids)

(a) 2015



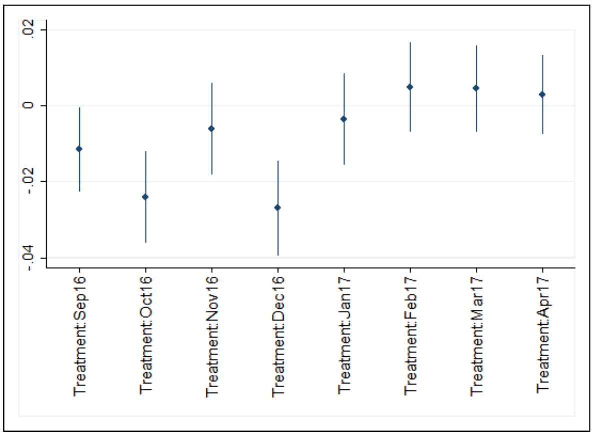


(b) 2014

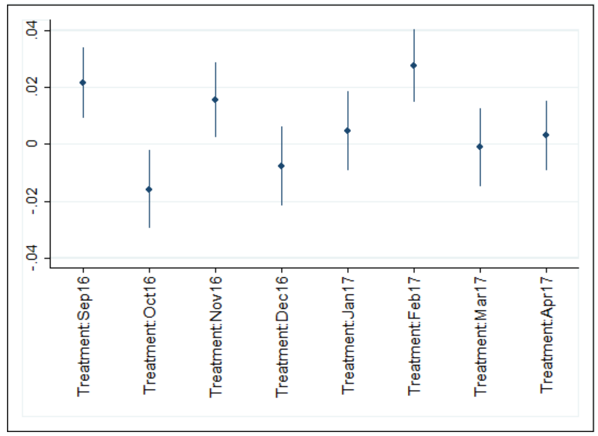
Notes: These two figures plot the log of Total Income (computed from Consumer Pyramids) and District GDP (from Indicus Analytics) for the years 2014 and 2015. The positive correlation between the two signifies that the two data sets are broadly consistent. In other words, districts with higher (lower) GDP are also the districts with higher (lower) total income. Plots are based on common 402 districts (roughly 413 districts are covered in CP excl. Delhi).

Figure 4: DiD, Monthly Trends: Total Income

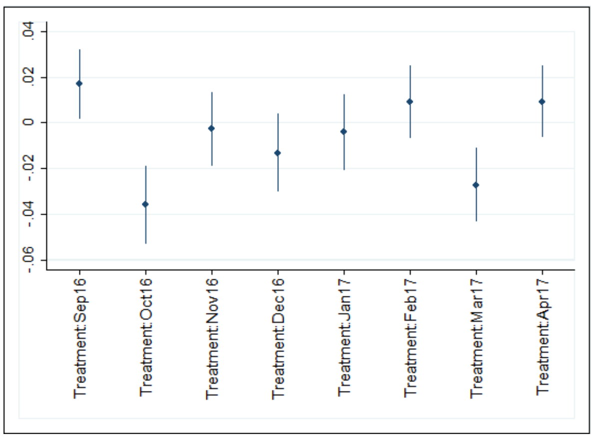
(a) Asset Class 1



(b) Asset Class 2



(c) Asset Class 3



(d) Asset Class 4

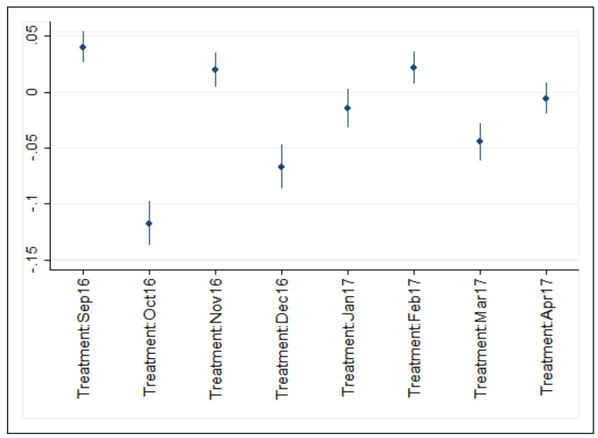
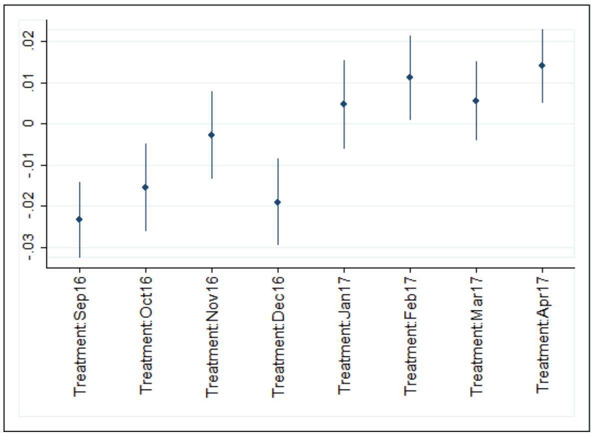
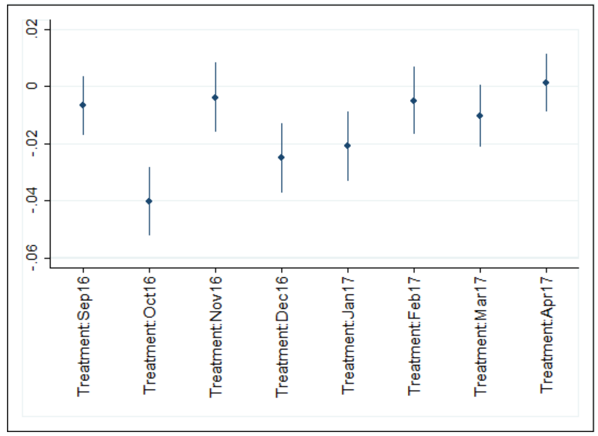


Figure 5: DiD, Monthly Trends: Total Expenditure

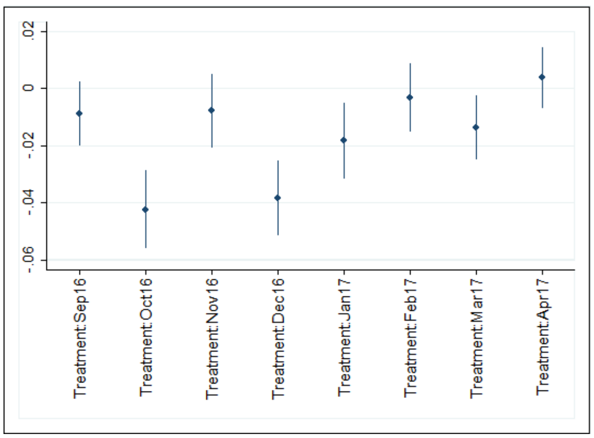
(a) Asset Class 1



(b) Asset Class 2



(c) Asset Class 3



(d) Asset Class 4

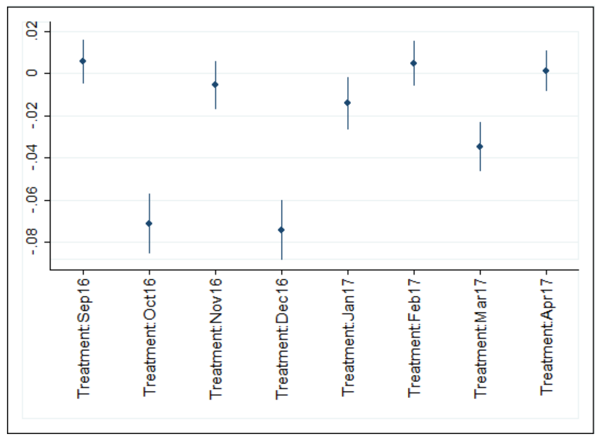
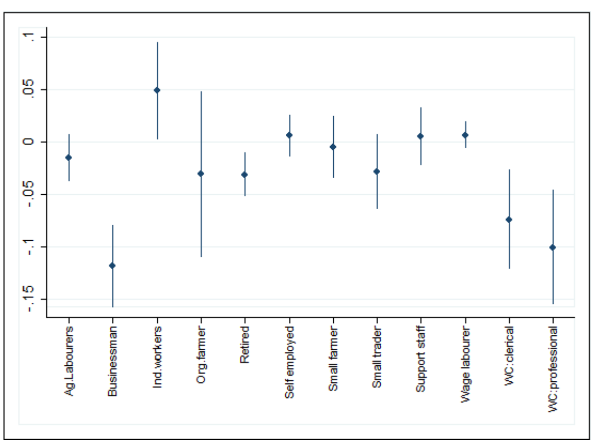


Figure 6: DiD: By Profession (December-2016)

(a) Income



(b) Expenditure

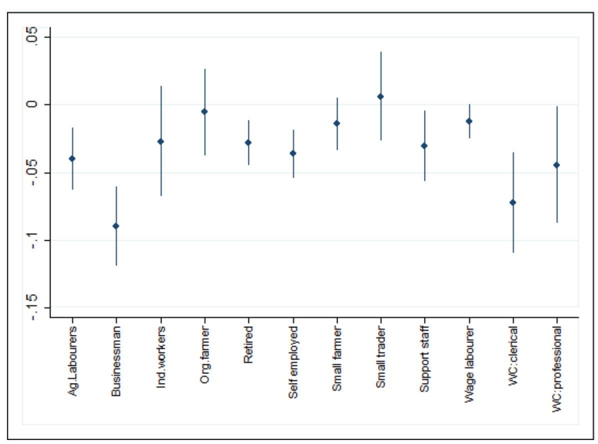
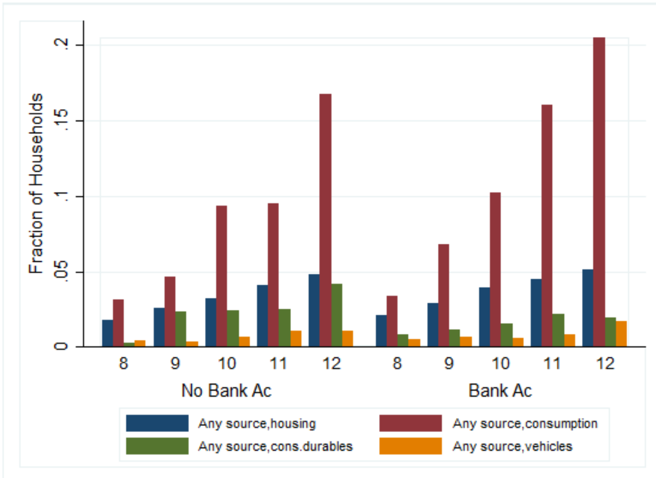
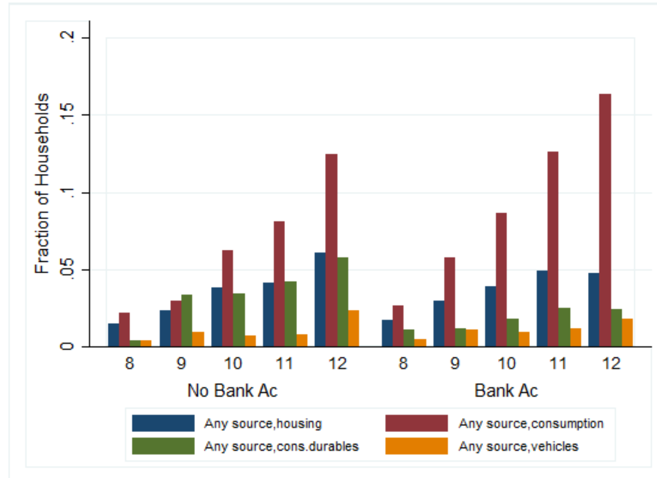


Figure 7: Borrowings (by purpose), by Asset Classes (Across Waves)

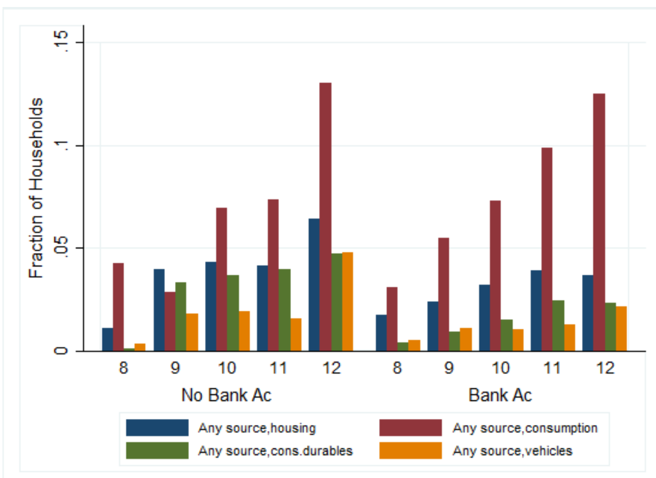
(a) Asset Class 1



(b) Asset Class 2



(c) Asset Class 3



(d) Asset Class 4

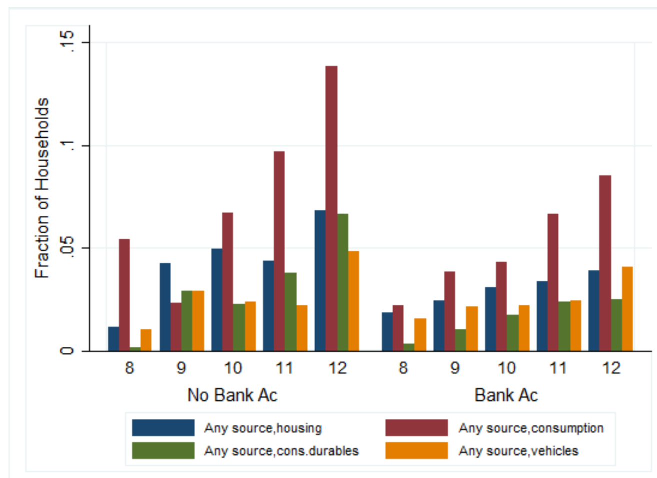
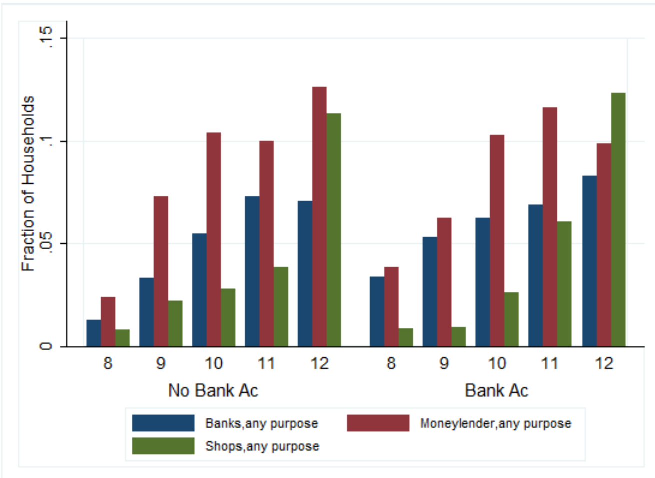
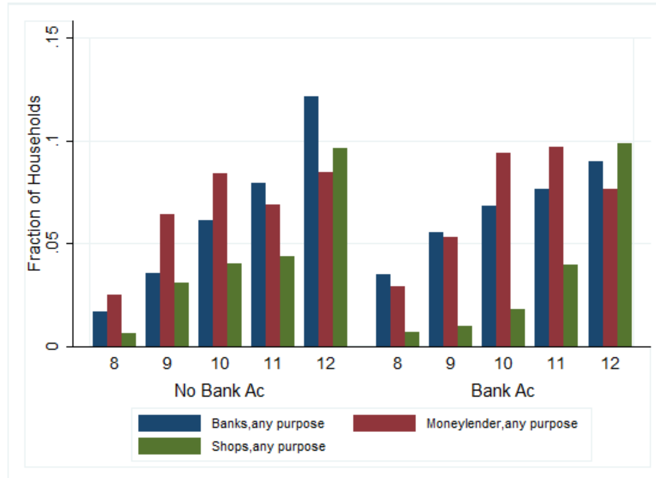


Figure 8: Borrowings (by source, any purpose), by Asset Classes (Across Waves)

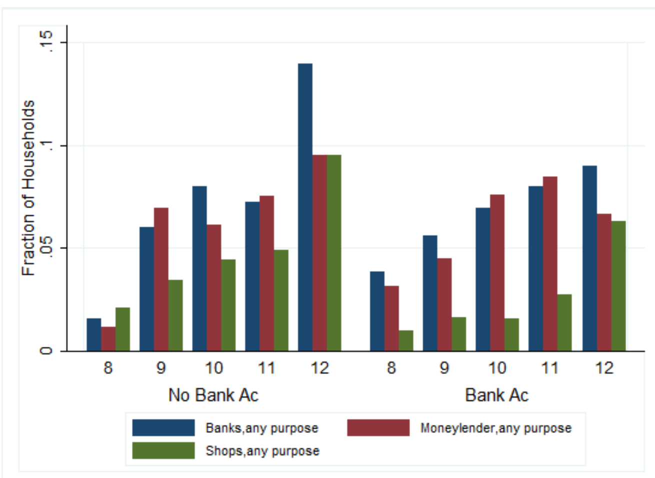
(a) Asset Class 1



(b) Asset Class 2



(c) Asset Class 3



(d) Asset Class 4

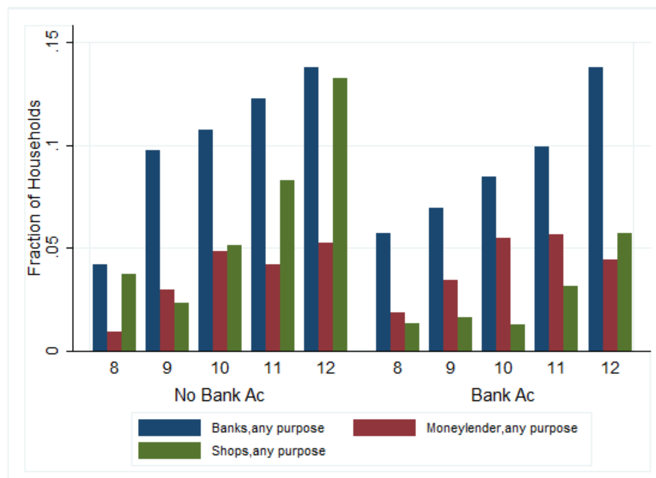
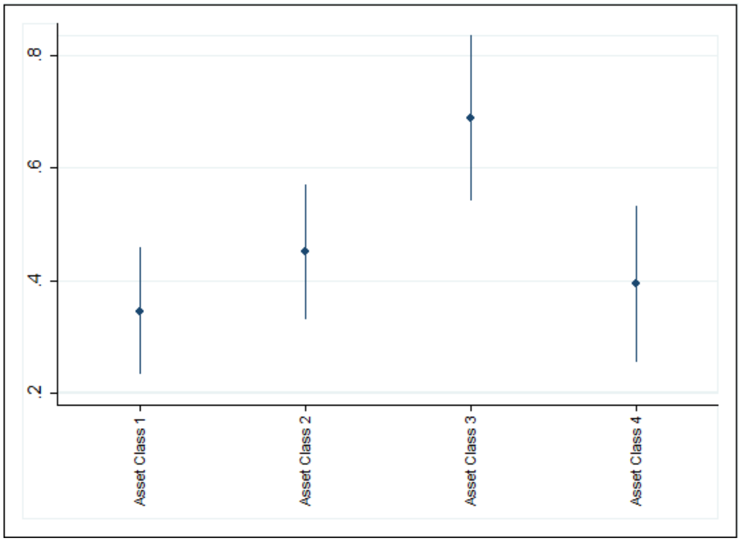
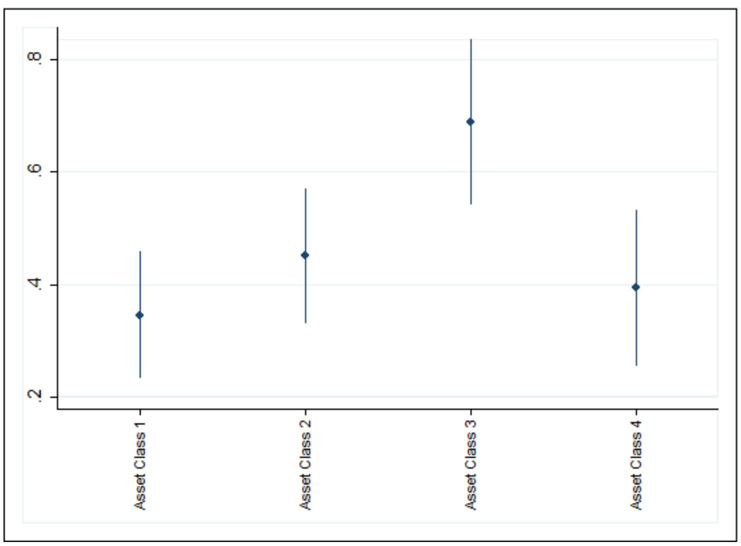


Figure 9: Logit Coefficients: Borrowings, Any source



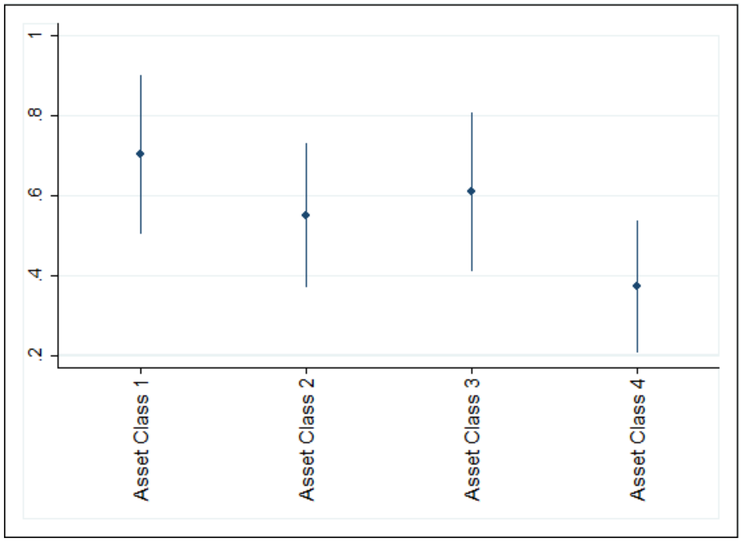
This figure plots the coefficient of the (treatment*post) in a logit regression. The coefficients tell us the relative probability of borrowing of households without bank accounts compared to households with bank accounts before and after demonetization.

Figure 10: Logit Coefficients: Borrowings, Banks



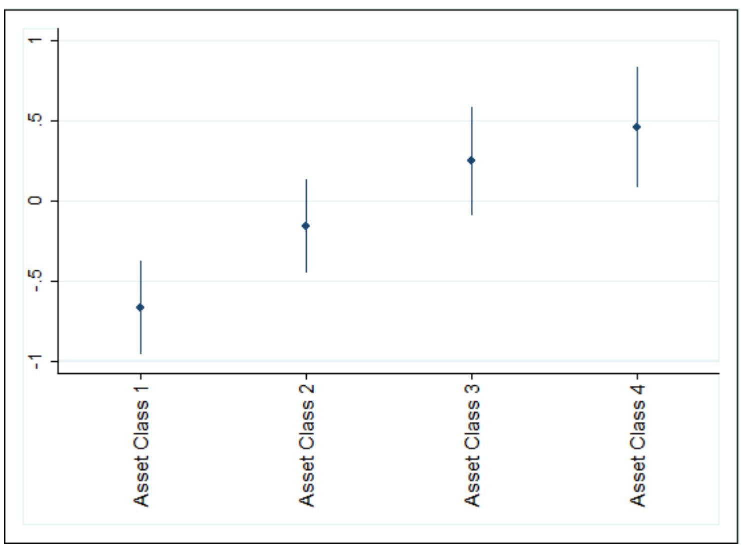
This figure plots the coefficient of the (treatment*post) in a logit regression. The coefficients tell us the relative probability of borrowing of households without bank accounts compared to households with bank accounts before and after demonetization.

Figure 11: Logit Coefficients: Borrowings, Moneylenders



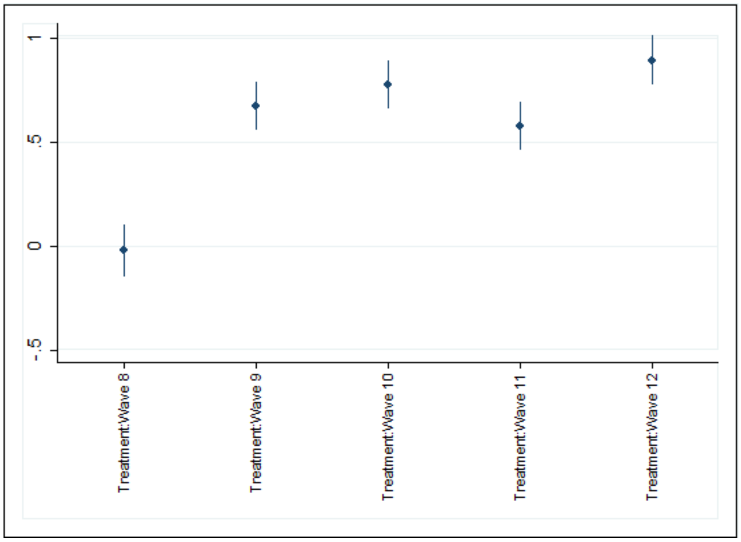
This figure plots the coefficient of the (treatment*post) in a logit regression. The coefficients tell us the relative probability of borrowing of households without bank accounts compared to households with bank accounts before and after demonetization.

Figure 12: Logit Coefficients: Borrowings, Shops



This figure plots the coefficient of the (treatment*post) in a logit regression. The coefficients tell us the relative probability of borrowing of households without bank accounts compared to households with bank accounts before and after demonetization.

Figure 13: Logit Coefficients: Borrowings, Any source (Wave-wise)



This figure plots the coefficient of the (treatment*post) in a logit regression. The coefficients tell us the relative probability of borrowing of households without bank accounts compared to households with bank accounts before and after demonetization.

Appendix

Table A.1: Household Monthly Income and Expenditure

Income Variables	**mean**	**sd**	**min**	**max**	**p25**	**p50**	**p75**	**p90**
TOTAL_INCOME	12606.0	8944.0	2042.5	41848.3	6230.5	9527.8	16339.9	26963.6
HH_INCOME_FROM_ALL_SOURCES_OF_HH	236.6	972.2	0	8857.4	0	0	0	508.2
HH_INCOME_FROM_ALL_SOURCES_OF_ALL_MEM	11961.7	8870.6	0	39232.8	5882.4	9140.6	15730.3	26088.8
HH_INCOME_FROM_WAGES_OT_BONUS_OF_ALL_MEM	11155.5	8622.7	0	39232.8	5456.0	8433.3	14886.5	24855.0
Expenditure Variables								
TOTAL_EXPENDITURE	7579.0	3332.0	2824.5	17243.2	5081.6	6807.1	9298.4	12779.7
EXPENSE_ON_FOOD	3727.1	1260.4	1469.9	6830.9	2767.4	3567.4	4510.1	5634.4
EXPENSE_ON_CEREALS_AND_PULSES	1001.6	358.5	363.0	1859.5	724.8	958.7	1244.0	1539.1
EXPENSE_ON_VEGETABLES_AND_WET_SPICES	453.0	224.8	97.9	1062.9	278.6	415.6	587.7	781.9
EXPENSE_ON_INTOXICANTS	213.7	233.8	0	823.5	0	148.4	338.7	590.8
EXPENSE_ON_CLOTHING_AND_FOOTWEAR	326.8	493.1	0	2447.8	0	49.1	479.7	1123.6
EXPENSE_ON_APPLIANCES	21.4	59.8	0	336.0	0	0	0	85.9
EXPENSE_ON_RESTAURANT	140.0	161.8	0	708.6	0	97.4	225.9	390.6
EXPENSE_ON_TRANSPORT	191.5	176.7	0	752.9	62.5	150.6	268.6	474.7
EXPENSE_ON_HEALTH	132.2	133.6	0	625.0	43.1	88.7	167.1	322.3
Observations	5061781							

Note: These figures are sample weighted averages for all households surveyed between Jan 2014 and Mar 2017. These figures refer to the pooled average over the entire sample in 2011-12 Rupees.

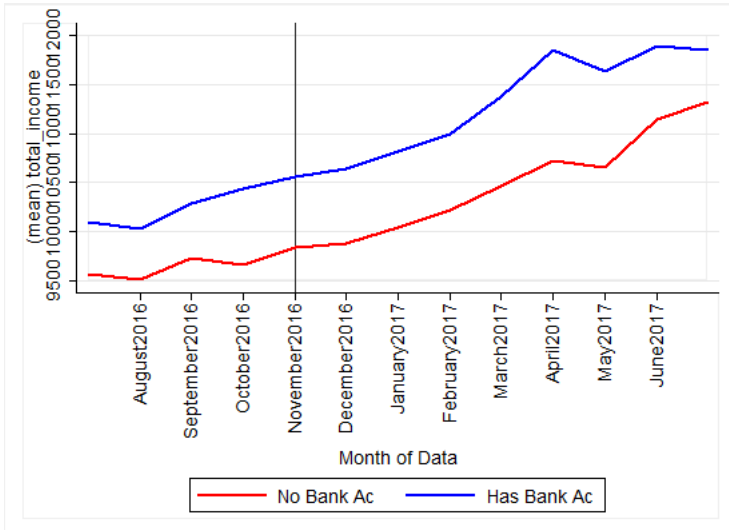
Table A.2: State-wise Pre and Post **Per Capita** Income and Consumption

	Total Hhd. Income		Wages		Total Hhd. Expen		Total Expen. on Food	
State	Pre-Demon	Post-Demon	Pre-Demon	Post-Demon	Pre-Demon	Post-Demon	Pre-Demon	Post-Demon
Jammu and Kashmir	1657.5	1688.3	1338.9	1334.2	1050.1	1024.9	480.2	479.2
Himachal Pradesh	2930.1	2946.0	2337.8	2346.8	2125.6	2083.5	939.1	921.6
Punjab	4208.9	3849.4	2858.0	2242.3	2520.7	2552.0	1210.2	1206.9
Chandigarh	6599.0	6661.0	3039.2	3318.3	3189.1	2954.0	1329.8	1216.4
Uttarakhand	4261.2	4377.4	3632.6	3684.2	2126.5	2214.8	1023.8	1013.1
Haryana	4153.2	3867.5	2450.5	2266.2	2622.7	2648.2	1138.1	1146.0
Delhi	3241.3	2718.6	2811.2	2276.4	1333.3	1302.4	649.9	638.4
Rajasthan	2390.0	2354.5	2138.2	2147.6	1478.4	1353.1	685.4	623.2
Uttar Pradesh	1821.2	2025.9	1600.3	1783.3	1279.1	1333.9	697.7	725.5
Bihar	1516.1	1599.2	1426.6	1491.5	1144.7	1166.3	686.7	679.4
Assam	1971.5	2133.1	1498.6	1640.6	1425.2	1617.0	670.5	757.2
West Bengal	1928.8	1985.4	1660.9	1710.9	1379.2	1364.4	744.0	750.7
Jharkhand	1293.6	1444.7	1219.7	1361.9	1020.5	1109.8	517.7	559.7
Odisha	1628.2	1597.1	1436.1	1404.9	1048.6	1077.6	502.8	502.6
Chhattisgarh	1698.5	1883.1	1486.1	1655.2	1081.3	1014.0	488.2	475.0
Madhya Pradesh	1787.0	1907.4	1555.3	1685.0	1058.6	1001.1	511.2	479.7
Gujarat	1887.6	1975.3	1521.2	1586.4	1515.9	1549.8	775.5	815.2
Maharashtra	3398.7	3407.0	2880.7	2854.9	1975.5	1951.3	865.9	880.9
Andhra Pradesh	3104.7	3067.5	2582.4	2516.4	2018.8	1906.1	987.2	987.9
Karnataka	2861.6	3004.0	2610.6	2739.4	1791.4	1829.2	894.0	907.1
Goa	4770.2	4926.8	3616.3	3773.2	2794.1	2883.4	1051.5	1093.4
Kerala	2695.0	2786.7	2194.5	2237.0	1890.4	1847.8	802.1	791.8
Tamil Nadu	2881.4	3142.8	2476.2	2706.6	1700.8	1918.4	847.5	973.4
Puducherry	3743.7	3181.2	2964.1	2481.1	1865.9	1806.7	812.1	805.3
Telangana	2596.4	2884.5	2207.1	2468.6	1640.2	1708.1	750.5	795.1
Total	**2841.0**	**2856.6**	**2221.7**	**2228.5**	**1723.1**	**1728.7**	**802.5**	**809.0**

Note: This tables reports the average Per Capita income and expenditure Pre and Post demonetization period in 2011-12 Rupees.
Pre-Demonetization Period refers to the months Sep 2016 and Oct 2016. Post-Demonetization Period refers to the months Nov 2016 and Dec 2016.

Figure A.1: Total HH Income, by No. of Bank Acs

(a) Level (Rs.)



(b) YoY (Percent)

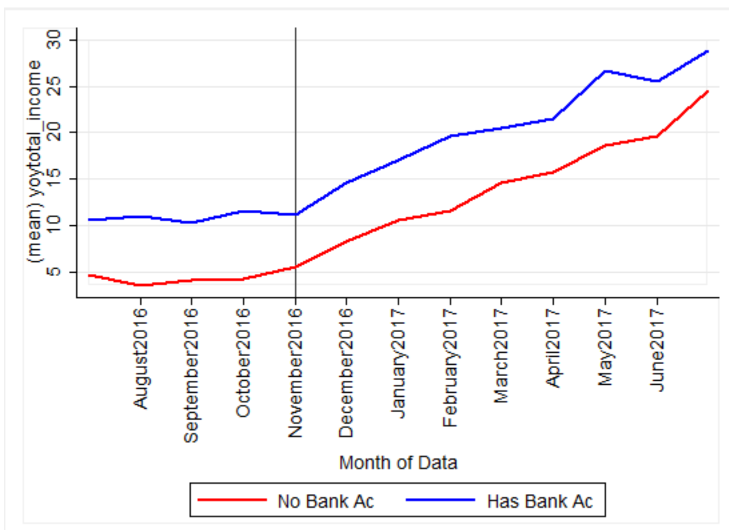
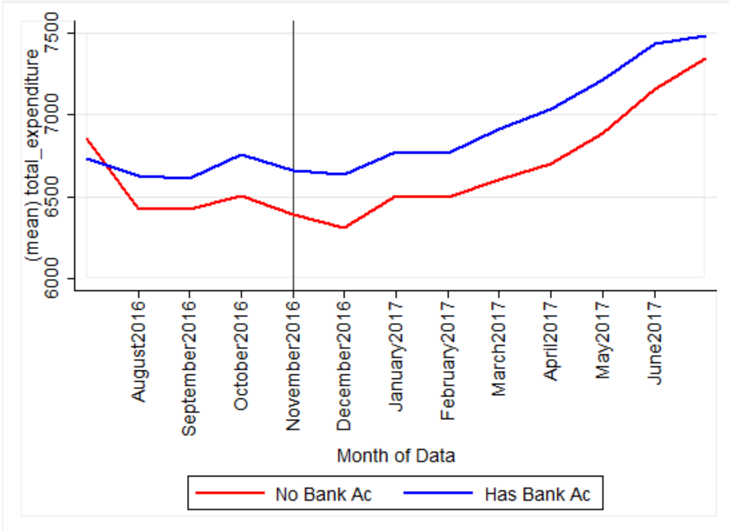


Figure A.2: HH Expenditure

(a) Levels (Rs.)



(b) YoY Growth (Percent)

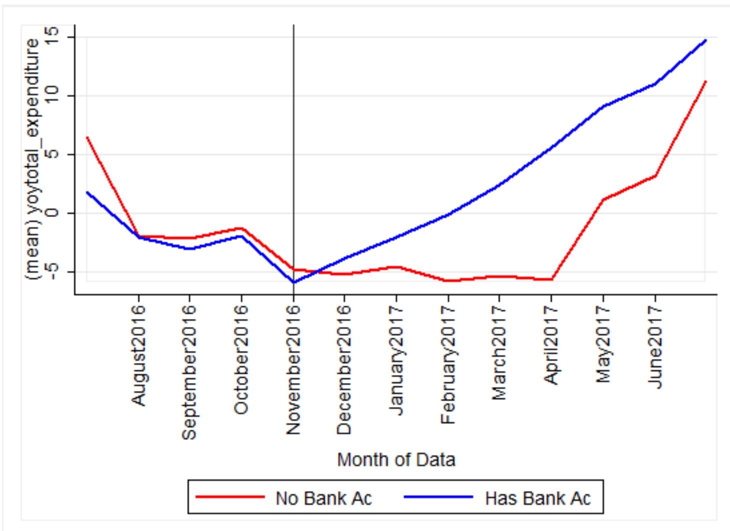
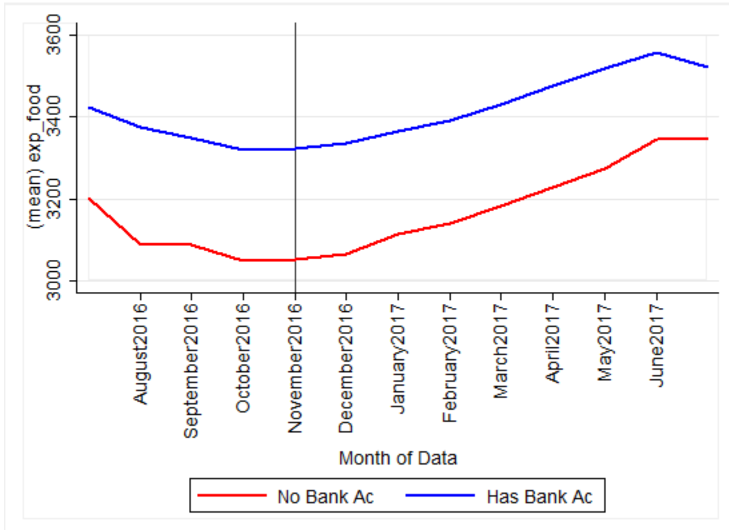


Figure A.3: HH Expenditure on Food

(a) Levels (Rs.)



(b) YoY Growth (Percent)

Figure A.4: Total HH Savings, by No. of Bank Acs