Impact of Demonetization on Household Consumption in India

January 3, 2023

Abstract

In November 2016, the Government of India made the two highest denomination currency notes invalid overnight. While this move was proposed for potential future benefits, it resulted in severe liquidity constraints for many households as these two notes constituted 86% of the total currency in circulation. In this paper, I study the impact of resulting liquidity constraints on household consumption using Consumer Pyramids panel data. I find that demonetization led to a decline in household durable and non-durable consumption in the initial months after demonetization. The decline was relatively higher for richer households. I also find that households increased borrowing after demonetization, particularly from money lenders. The increase in borrowing was relatively higher for poorer households. Focusing on heterogeneity among farmers, I show that the use of credit was higher for those households who rely more on cash. The results suggest that while richer households reduced their consumption because it came at a lower utility cost to them, poorer households had to rely on informal credit to maintain their consumption.

Keywords— Demonetization, Consumption, Informal credit

1 Introduction

In a landmark decision, the Government of India made invalid the two highest denomination currency notes of 500 and 1000 rupees (approximately \$7.5 and \$15 respectively) on 8th of November 2016. These two currency notes constituted 86% of the total currency in circulation at that time. In their place, new notes of 500 and 2000 rupees were to be issued. Figure 1 shows the massive decline in currency in circulation after demonetization. Unlike most of the other demonetization episodes in the world, this move was passed with the objectives to curb black money and counterfeit currency and nudge the economy towards formalization.

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While there might be the potential long term benefits mentioned above, wiping out 86% of the currency overnight in a cash-dependent economy came with short term costs. People had to go to banks to deposit the old currency in their bank accounts or to exchange the old notes for new notes. Inadequate supply of new currency and the limited access to commercial banks implied that people had to stand in long lines to get access to the new currency, and still struggled to get the required cash (Banerjee and Kala (2017), Zhu et al. (2017)). These costs could be detrimental for the household well-being, particularly since 85% of the workforce is employed in the informal sector (Kolli and Sinharay (2011)). These occupations[1] mostly run on cash, and people working in the informal sector are less likely to use banking services.[2] Although there has been evidence of demonetization leading to a decline in overall economic activity and employment (Chodorow-Reich et al. (2020), CMIE (2018), State-Of-Working-India-Report (2019)), the impact of such macroeconomic shocks at the household well-being ultimately depends on the mechanisms households have to deal with the shocks (Skoufias (2003), Thomas et al. (1999)). In this paper, as a measure of household well-being, I study the impact of demonetization on household consumption. I also study the heterogeneity in the effect across households and examine the coping mechanisms used by the households to deal with the shock.

In development economics literature on consumption smoothing, almost all the work has been done on the consumption shocks working through income shocks, that is, a decline in income potentially leading to a decline in consumption (Townsend (1995), Morduch (1995) among others). Demonetization is a unique shock in this aspect because while it can affect income, it can also affect consumption more directly even without affecting income. Lack of cash can affect income if employers did not have the cash to pay their employees, resulting in a lack of employment (Guérin et al. (2017)). Similarly, traders' income could be affected if the demand and supply of their goods were affected due to lack of cash. Consumption can be affected without the impact on income if people just did not have the required cash for their day-to-day purchases. However, it is not obvious that there would be an impact on household consumption. In particular, one mechanism that households could have used is credit. Even though the higher denomination notes were not valid, the smaller denomination notes were still valid. Furthermore, some people may have a higher amount of new currency than what they need, so people could potentially borrow in new currency notes as well. For the income channel also, income may not be affected if supply and demand operations could have run on deferred payments.[3]

To study the impact of demonetization, I use Consumer Pyramids data from Centre for Monitoring Indian Economy (CMIE). This survey covers roughly 160,000 households all over India. Starting from January 2014, each household is visited once every four months and information about household demographics, occupation,

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[1]Informal occupations are those that fail to accord social security to the employees. Examples include farmers, agricultural laborers, daily wage laborers, small traders etc.

[2]Many notable economists including Amartya Sen, Kaushik Basu, Paul Krugman and Raghuram Rajan also predicted severe impact on household welfare (Hindustan Times, 5th Sep 2017).

[3]Some people also found alternate ways to earn money during demonetization. For example, people were being paid to stand in lines to exchange the notes (The Guardian, 27 Nov 2016)

income and consumption expenditure is collected. Income and non-durable expenditure data are collected for each month while other information is collected once every four months. While the income and non-durable expenditure information is available in terms of actual amount earned or spent, the durable assets and borrowing data are available only in terms of binary variables. These variables indicate whether or not household bought an asset or has any outstanding borrowing.

Since demonetization was implemented for the entire country with no exogenous cross sectional variation, any cross-sectional comparison would impose strong assumptions to estimate the impact of the shock. In order to relax these strong assumptions implied by cross-sectional comparisons, I rely on the time series variation for estimation. The shock was totally unanticipated, so people had no time to prepare beforehand. Since the shock is at the aggregate level, regression at household level would lead to incorrect standard errors and hence misleading inference (Hansen (2007)). To tackle this problem, I follow the advice in the econometric literature (Amemiya (1978), Hansen (2007)) and estimate a two step model where I first estimate the monthly time series of the outcome variables after controlling for household characteristics. I use these estimated monthly averages as dependent variables and use a 12-months window to estimate the effect after demonetization. I restrict the time period for estimating the effect of demonetization, as the trends are likely to be similar in a small window around demonetization.

Using the above method and data, I find that demonetization led to a 4.4 percentage points decline in the probability of buying durable goods from a baseline of close to 10 percent in the period six months before demonetization. Furthermore, it also led to almost 10% (834 rupees) decline in the non-durable consumption expenditure. On the one hand, since the poorer and informal sector households rely mainly on cash and have lower access to banking services, they might be more affected. On the contrary, these households, due to their low consumption level, also have higher cost of a further decline in consumption,[4] so they might be willing to incur higher transaction costs to get the requisite cash. They may also have a higher incentive to use any consumption smoothing mechanisms. I find that the decline in consumption, particularly the non-durable consumption expenditure, is higher for the relatively richer households and the formal sector households, while households in the bottom 20% of the expenditure distribution show the least effect on non-durable consumption expenditure.

I examine the mechanisms used to deal with the shock, particularly by the relatively poorer households. The probability of having an outstanding borrowing increases by 28% from a baseline of 7.5 percent. Although the borrowing increases from various sources, the largest increase is observed for borrowing from money lenders. The probability of having outstanding debt increases by a higher amount for informal workers and for relatively poorer households. This result suggests that relatively poorer households used credit to deal with the shock and maintain their non-durable consumption while the relatively richer households did not incur the cost of

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[4]Assuming diminishing marginal utility, the loss in utility from the same decline in consumption at lower levels would be much higher than the loss in utility from the same decline in consumption at higher levels.

borrowing and instead reduced their consumption temporarily after demonetization.

One explanation of the decline in consumption could be a corresponding decline in income and in particular, a differential change in income for the richer and poorer households. However, I cannot reject that there is no effect on income. I also do not find evidence that the incomes are changing differently for the richer and poorer households. This result suggests that the consumption is declining due to the liquidity constraints- that is, households not having the requisite cash for their day-to-day purchases.

To test whether the use of credit was higher among households who rely more on cash, I compare farmers who consume their own grown food to those who do not consume their own grown food. Farmers who consume own grown food, presumably deal less in cash as they need to do fewer transactions as compared to farmers who do not consume own grown food. Comparing the two groups before and after demonetization, I find that the probability of borrowing from money lenders increases *by 4 percentage points less* for 'subsistence households' as compared to 'non-subsistence households', suggesting that the use of credit was higher among more cash-constrained households.

My paper makes the following two contributions in the literature. First, it contributes to the literature on the impact of macroeconomic shocks on household economic outcomes and how households respond to these shocks (Thomas et al. (1999), Fallon and Lucas (2002), Skoufias (2003), McKenzie (2003), among others). Thomas et al. (1999) study the impact of the Indonesian financial crisis and find that the households were negatively affected as the share of food in the household budget increased, and households also had to cut down on education expenditures. Fallon and Lucas (2002) provide a review of the evidence on the impact of national-level economic shocks on household economic outcomes. Skoufias (2003) reviews the evidence on coping strategies used by households to deal with economic crises. McKenzie (2003) studies the impact of the 1995 Mexican peso crisis on household outcomes. In terms of dealing with the shock, Acquah (2016) and Acquah and Dahal (2018) highlight the role of borrowing from ROSCAs to deal with the crisis in Indonesia. My paper adds to this literature by studying a unique macroeconomic shock which rules out any ex-ante preparation by the households, including their savings to deal with the shock.

Second, my paper contributes to the evidence on the impact of the 2016 demonetization in India. There has been a lot of debate regarding the impact of demonetization. Many studies have come out on the impact of demonetization in various parts of India. The closest studies to the current project are Chodorow-Reich et al. (2020) and Karmakar and Narayanan (2019). Chodorow-Reich et al. (2020) study employment and night light intensity by the geographic distribution of demonetized notes and new notes. They find that employment and nightlights-based output in high shock areas decline by 2 p.p. after demonetization relative to low shock areas and these effects dissipate over the next few months. However, there are concerns that the distribution of new currency notes may not have been random (Lahiri (2020)). I also find that the employment levels before

demonetization were very different in the high shock and low shock areas,[5] so the low shock areas are unlikely to represent the counter-factual of high shock areas in absence of demonetization. I instead rely on time series variation, and analyze impacts on household consumption and household coping mechanisms.

There is another simultaneous work by Karmakar and Narayanan (2019) also looking at impact at the household level using the same CMIE data. They find that households without bank accounts experienced significant decline in income and expenditure in December 2016 compared to households with bank accounts, and they also report the increase in credit to deal with the shock. In addition, I also show the relationship between the effect on consumption and the effect on borrowing based on the expenditure quintiles. This relationship helps us understand while some households could afford to reduce their consumption and not rely on coping mechanisms such as credit, other households had to rely on the borrowing from the money lenders in order to maintain their consumption levels. Apart from these differences, my work also looks at durable consumption and the heterogeneity in borrowing by difference in reliance on cash using data on subsistence agriculture.

Among other studies on demonetization, Aggarwal and Narayanan (2017) find a decline in domestic agricultural trade as a result of demonetization. Banerjee and Kala (2017) find that the wholesale sales fell by 20% in Bangalore. Zhu et al. (2017) report negative impact of demonetization on household economic outcomes. Chadha et al. (2017) and Chand and Singh (2017) report that demonetization may not have had an adverse impact on agriculture. Guérin et al. (2017) report that the strength of informal networks increased after demonetization. However, most of these studies analyze the impact on household economic outcomes at a small scale. Apart from having small sample size and being based in a particular region, most of these studies are also based on data at two points in time. My paper contributes to this debate by analyzing national-level data where I have month-to-month data on household economic outcomes.

2   Background

Demonetization was announced on the 8th of November, 2016 at 8:15 pm by the Prime Minister of India. From midnight onward, all 500 and 1000 rupees notes were going to be illegal, which accounted for roughly 86% of total currency in circulation. Other currency notes included 1, 5, 10, 20, 50 and 100 rupees notes and they along with coins constituted the rest 14% of the currency. The shock was completely unanticipated. People were given time till 30th of December, 2016 to deposit the banned currency notes in their bank accounts or post-office accounts. They were also allowed to exchange the old currency notes for the new ones by visiting a bank branch. However, to encourage the un-banked population to open a bank account, this over-the-counter

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[5]I was not able to get the currency chest data used by Chodorow-Reich et al. (2020). For this analysis, I used the map showing the intensity of demonetization shock provided in their paper. The shock variable had seven categories, I classified the three highest shock categories as high shock areas and the three lowest shock categories as low shock areas. The employment data, however, is the same as that used in their paper.

exchange was stopped after 25th November. One major stated objective of demonetization was to curb black money. Black money is the money on which people manage to evade paying taxes or the money which is acquired through corrupt practices. The idea was that people hold a lot of black money in these two currency notes and by making them illegal, this black money would become useless for them. To discourage people from depositing their black money in banks, it was also announced that all deposits above 250,000 rupees were to be subjected to potential scrutiny.

Another objective was to attack counterfeit currency. Here also, the idea was that a lot of counterfeit currency exists in these two currency notes which is used to support terrorism and by banning the two notes, this counterfeit currency would not be used. A third objective which actually gained more importance later on was that demonetization was going to be a nudge towards more digitization. People were being encouraged to use more electronic modes of payment. The idea here was that the digitization would lead to a more formal record of transactions which would lead to higher tax collection for the government.

The implementation of the policy involved considerable chaos. New currency notes of 500 and 2000 rupees were issued. However, the supply of the new currency was not adequate (Mazumdar (2016)). The new notes also did not fit the existing ATM machines and the machines had to be made compatible which further delayed the restoration of liquidity (Tharoor (2016)). Due to inadequate supply of new currency, there were limits on how much money could be withdrawn from a bank or from an ATM machine by an individual in a day. Furthermore, the rules regarding the limits and various exemptions (for example, for weddings) were changed roughly 50 times in the seven weeks following the announcement (Banerjee et al. (2018)) which also added to the confusion among people.

To get the new currency notes, one needed to go to a commercial bank branch or use an ATM. However, people had to wait in long lines to be able to get new currency as there are only around 14 commercial bank branches per 100,000 adults in India (World Bank 2016). In comparison, there are around 32 commercial bank branches per 100,000 adults in the US, and India ranks 74th in the world. The access to banks is even more limited for rural areas. While around 70% of the Indian population lives in rural areas (Census 2011), these areas have only 37% of all commercial bank branches (RBI, June 2016). All these factors implied that people faced severe cash shortage immediately after demonetization.

3 Data

To study the impact of demonetization in India, I use Consumer Pyramids Survey Data collected by Center for Monitoring Indian Economy (CMIE). In this section, I lay out the key features of the data, define how I measure the key variables and also lay out some advantages and limitations.

The survey interviews around 160,000 households, almost all over India.[6] Households are selected through

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[6]The areas not covered are Arunachal Pradesh, Nagaland, Manipur, Mizoram, Sikkim, Andaman & Nicobar Islands,

a stratified multi-stage survey design. Starting from January 2014, each household is visited once every four months.[7] This 4-month period is called a wave.[8] While the households are visited once every four months, income and non-durable consumption expenditure (both in rupees) information is obtained for the previous four months, thus giving a monthly time series of these variables for each household. While the income is also available for each household member, expenditure information is available only at the household level.

Household income information is further divided into imputed income (value of production used in self-consumption), income from transfers, profits from sale of assets, wages, pension, dividends and interest. The expenditure data includes subcategories such as food, education, health, clothing and footwear, cosmetics, recreation, power and fuel. These categories are further subdivided into finer categories. For example, the expenditure on food is also subdivided into expenditure on pulses, whole grains, edible oils, ghee, among other food products. The survey also contains other information including demographics, education, occupation and labor force participation of each member of the household and assets and liabilities at the level of household. Household members information about whether or not they have a bank account, debit or credit card is also available in the survey. These variables are available only once every four months for a household, that is, at the time of the survey.

3.1 Measures

For income and non-durable consumption expenditure, while the information is collected for each month by asking about the previous four months individually, I find evidence that households seem to be reporting the income of previous four months based on their current circumstances. I show the evidence for this pattern in the data appendix. Due to this bias in the reporting for the previous months, I rely only on the most recent available information. For example, I rely on households being interviewed in February for their information on January income and non-durable expenditure.[9] Therefore, the January averages are constructed from households interviewed in February, February averages from households interviewed in March and so on.[10]

One major advantage of the data is the availability of observations for each month. Since demonetization was a short term shock, it is important to have information for each month as having data say, a year apart

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[7]Therefore, every month, roughly one fourth of the households are interviewed.

[8]The data is still being collected for further waves. However, for my analysis, I use data till the end of 2017.

[9]This is another difference in comparison to the work by Karmakar and Narayanan (2019).

[10]Limiting to only the most recent month of data implies that the sample is the same only once every four months and for any consecutive four-month period, the samples are different from each other. This approach could be problematic for estimating the effect if the samples of different months are very different from each other, say in terms of proximity to banks or their income and expenditure levels. Appendix table A.2 provides the averages of characteristics of the household head and income and expenditure levels of the households by the month of survey for the full wave before demonetization, that is, May-Aug 2016. While the income and expenditure levels show the combined effect of seasonality and of the households interviewed in that particular month, we can see that the values of the other variables are very similar for households in different months. Furthermore, the regressions control for household fixed effects to account for time invariant differences between households.

may show no effect because the liquidity would have been restored. In this case, even if I won't have the same households in every month but I still have observations for one-fourth of the sample in each month from which I can take out the time invariant fixed characteristics as well. Having information in each month allows us to graphically observe the changes, if any, in the variables. Further, observing the same households over time is another advantage as it helps us to see the behaviour of same households before and after the shock. Having panel data also allows us to control for household unobserved characteristics that are fixed over time and helps tease out the effect of the program.

While there are these advantages of the data in studying the impact of demonetization, there are also some disadvantages. One major limitation is that assets and liabilities information is available only in terms of binary variables. For liabilities, the data only tells us about whether the household has any outstanding borrowing from a particular source for a particular purpose. It does not contain any information about the amount or the interest rate of the loan taken. Similarly, the saving and investment information is also available only in terms of whether the household has saved or invested in a particular source or not. Similarly, while the non-durable goods expenditure is available in exact amount, the survey does not tell us about the durable expenditure. Durable goods expenditure such as purchase of TV, refrigerator etc. is available only in terms of Yes or No answers to the questions of whether the household purchased any particular asset in the last four months.

3.2 Summary statistics

Some basic sample properties are given in appendix table A.3.[11] The average years of schooling of household head are roughly 7.5 years. Only 3.5% of the households have a credit card which also shows how cash-dependent Indian economy is. Table 1 provides the sample means of the main outcome variables separately for rural and urban areas, before and after demonetization. We can see in the table that urban households have higher income and expenditure levels, and own more durable assets as compared to rural households. The probability of borrowing is much higher after demonetization in both rural and urban areas. The expenditure and income levels are also higher after demonetization. However, it is to be noted that the pre-demonetization averages are for all the months from January 2014 to October 2016 and since the incomes have been growing over time, these averages also include the smaller amounts of 2014 and 2015. For the analysis, I use information on all the households and do not restrict to the balanced panel. However, my results are not affected by this choice and the graphical evidence for balanced panel sample is available in the appendix figures, separately for each variable.

As a verification check of the CMIE data, I compare the average per capita expenditure in rural and urban

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[11]The data has 31% rural households and 69% urban households. As per CMIE, "The larger urban sample size reflects the greater diversity in town-size and the approach of the sampling methodology to capture this diversity adequately". However, using the survey weights provided, the data is representative at the national level. The survey is not able to interview all the households in all the waves. On average, a household's information is available for roughly 9.9 waves out of 12. For roughly one-fourth of the sample, the information is available for all the waves.

areas for 2014 with the same average in NSS Consumption Expenditure data for 2012 (which is the closest to the years for which the CMIE data is available). The growth in expenditure from 2012 NSS data to 2014 CMIE data is comparable to the growth in expenditure reported from NSS 2010 and NSS 2012 data. This comparability of the estimates suggests that the CMIE data estimates are not far off from the other national level data-sets in India which have been used in the literature. Furthermore, when we look at the average monthly expenditure on clothing and footwear, we see that there is an upward jump in clothing and footwear expenditure in the month of Diwali. Diwali is a major Indian festival which generally takes place in the months of October or November. During Diwali, people buy new clothes and that increase shows up in Figure A.9 in exactly that month when Diwali occurs, that is, in October in 2016, in November in 2015 and in October in 2014. I also provide further verification tests for different variables in the Results section.

4   Estimation

Since demonetization was a national-level shock, there is lack of exogenous cross-sectional variation. There have been few attempts at using cross-sectional variation and there are some other candidates of potential variation as well, but using them to estimate the impact of the shock require very strong identifying assumptions. Chodorow-Reich et al. (2020), for example, rely on the variation in the distribution of new currency notes. However, there are concerns that this variation may not have been random as the Reserve Bank of India (RBI) 2017 annual report also suggested that the distribution was according to a prior plan (Lahiri (2020)).

Other potential sources of variation include comparing people with and without bank accounts (used by Karmakar and Narayanan (2019)) or areas with higher and lower number of bank branches per capita. While it is plausible that areas with higher number of bank branches per capita and people with bank accounts had easier access to new currency notes, these comparisons suffer from strong endogeneity concerns. The people with bank accounts are likely to be economically different from people without bank accounts. Similarly, the areas which have higher number of bank branches are likely to be economically better off as compared to areas with lower number of bank branches per capita. Therefore, these areas could also have different levels of demand for new currency. If the currency demand is very different, the extent to which these areas are differently affected by the shock is not obvious. Therefore, while these comparisons can provide heterogeneity tests,[12] the validity of these comparisons providing causal impact of the shock require hard-to-justify exogeneity assumptions. To relax these assumptions, I rely only on the exogeneity of the timing of the shock and use time series analysis. Relying only on time series variation comes with its own problems. In particular, with this comparison, we don't get to observe the behavior of a control group during this time period. However, the magnitude of this shock allows us to learn something about its impact from just the time series comparison too, as I'll show in the figures below.

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[12]I provide the heterogeneity results by the availability of bank branches per capita in the appendix.

One way to estimate the model would be to use the household-month level data (that is, each observation being a household-month combination) and do the time-series analysis (that is, include and estimate the coefficient of a dummy for post-demonetization). While this approach gives valid estimates subject to identifying assumptions, it can lead to biased standard errors, and hence, misleading inference. This happens because the treatment varies only at month level and not at household level, that is, the months after demonetization represent treatment while months before demonetization don't. In other words, the treatment indicator D does not have any i subscript, it only has a t subscript. The problem is similar to the 'clustering problem' which arises in Applied Econometrics whenever the level of treatment is different from the level at which data is used in the regression. For example, if we are evaluating a treatment which varies at state level using household level data, we would need to cluster the standard errors at state level as well.

In this set up, the corresponding way of dealing with this bias in inference would be to cluster the standard errors by month. While that is a reasonable approach, clustering is more intuitive for cross-sectional entities such as state and less so for time periods. Therefore, I follow the advice in Econometrics literature (Amemiya (1978), Hansen (2007)) which instead suggest aggregating the data at the level of treatment to be a more conservative approach. Here, this method implies aggrgating household data at monthly level and then using that data for the final regression. For aggregating the data at monthly level, instead of using a simple average of all households for each month, we can actually do better by controlling for household level characteristics and using the estimated month effects as the monthly aggregates for the regression. I then use these estimated monthly averages as dependent variables and use a 12-month window to estimate the effect after demonetization.

This two step methodology in terms of estimation equations can be seen below. The first step is to use household level data and estimate monthly averages after controlling for household characteristics.

$$y_{it} = y_t + \rho X_{it} + \lambda_i + \mu_{it} \tag{1}$$

In this equation, y_{it} refers to the outcome variable for household i in month t, X_{it} refers to the household characteristics, λ_i refers to the household fixed effect, and y_t refers to the monthly average. From this regression, I estimate the monthly averages ($\hat{y}_t$) after controlling for household characteristics which change over time and household fixed effects. I then use these estimated monthly averages as outcome variable in the time-series regression. Since the estimated variable is being used as the outcome variable and not as an explanatory variable, measurement error due to estimation does not pose any issue.

$$\hat{y}_t = \alpha + \lambda_M + \gamma X_t + \delta Post_t + \delta_1 1_{t<t^*-6} + \delta_2 1_{t>t^*+6} + \psi t + \epsilon_t \tag{2}$$

Here, in equation 2, $\hat{y}_t$ is the estimated outcome variable for month t from equation 1. λ_M is the calendar month fixed effect to control for seasonality, X_t refers to the controls for the time series regression, t^* is the

month of the shock (November 2016).[13] $Post_t = 1_{t \geq t^*}$ is a dummy which takes the value 1 for months after October 2016 and 0 otherwise. As demonetization was announced in the beginning of November, I consider November also as a part of the post-demonetization period. $1_{t < t^* - 6}$ is a dummy variable which takes the value 1 for months before April 2016.[14] Similarly, $1_{t > t^* + 6}$ is a dummy variable which takes the value 1 for months after April 2017. I include these dummies so that the effect of the shock is estimated from a narrow window around demonetization. Another way to estimate the effect from a 12-month window around demonetization would be to use only these 12 months of data. However, using only 12 months of data won't allow us to estimate seasonal (calendar month) effects.[15] ψ allows for a linear time trend in months. For robustness, I also test the results based on different bandwidths around demonetization.

As mentioned earlier, another way to estimate the effects of the shock could be to cluster the standard errors at the month level and avoid this two-step process altogether. The results from this approach are available in the appendix tables and are not different from the results from the two-step estimation procedure. I primarily use the two-step estimation as the literature recommends this method due to it being more conservative.[16]

The assumption for estimation is as follows:

$$E(\epsilon_t | \lambda_M, X_t, 1_{t < t^* - 6}, 1_{t > t^* + 6}) = 0$$

In other words, during the 12 months window around demonetization, after controlling for the linear time trend and other household level characteristics, the only thing that was different for months after October 2016 was demonetization. This assumption would be violated if there were some other major shock around this time which affected the household outcomes. But the other major shock around this time was Goods and Services Tax (GST) and it was passed in July 2017 which is captured in the dummy for six months after demonetization. Similarly, the increase in salaries of government employees passed by Seventh Pay Commission were also being given out from mid-2017 (Press Information Bureau, Government of India, July 7, 2017). Hence, this assumption is not going to be violated by these two other shocks. Another concern would be if the households knew about the shock in advance and if they changed their behavior but as mentioned earlier, the shock was completely unanticipated and this concern is unlikely to bias the estimates.

I control for household level fixed effects to control for household characteristics that are fixed over time.

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[13]Seasonality is particularly important in this context as a significant proportion of workers are in agriculture whose income is likely to be high in certain months. If seasonality is not accounted for, there is likely to be bias in the estimates. For example, if say consumption is high every year in October and lower in November, it may seem like an effect of demonetization while it may actually be due to seasonality.

[14]In the time series estimation from the household data, I take October 2016 as the base month and all other values are relative to October 2016. Therefore, when I take six months before the shock, I do not have October's data and I use April-September 2016.

[15]The coefficients do not change if I first de-seasonalize the data and then use data for these 12 months to estimate the effect of demonetization.

[16]To account for the serial correlation in standard errors, I use the Newey-West correction and the results do not change based on this specification.

For controlling for the wealth of the household that could potentially change over time, I control for the number of various durable assets that the household owns. In the absence of actual amount of wealth data, I use the ownership of various assets as proxy for the household wealth.

4.1 Estimation of Heterogeneity

I use the same two-step procedure to test for heterogeneity in my results. First, from the household level regression, I estimate two monthly time series. For example, for two groups, S and T:

$$y_{ijt} = y_{jt} + \rho X_{ijt} + \lambda_i + \mu_{ijt}$$

where y_{ijt} refers to the outcome of household i in group j in month t. Using the household data, I estimate two times series ($\hat{y}_{jt}$), one for group S and the other for group T.

These estimated time series are then used as the outcome variable in the second regression to estimate heterogeneity.

$$\hat{y}_{jt} = \alpha + \beta GroupS_j + \delta Post_t + \delta_1 GroupS_j * Post_t$$
$$+ \phi_1 1_{t<t^*-6} + \phi_2 1_{t>t^*+6} + \phi_3 GroupS_j * 1_{t<t^*-6}$$
$$+ \phi_4 GroupS_j * 1_{t>t^*+6} + \lambda_M + \gamma X_t + \gamma_1 X_t * GroupS_j$$
$$+ \psi t + \psi_1 t * GroupS_j + \epsilon_{jt}$$

and at the household level:

$GroupS_j$ takes the value 1 for households in group S and 0 for households in group T. $Post_t$ takes the value 1 for months after October 2016 and 0 otherwise. $GroupS_j * Post_t$ refers to the interaction between group S and post dummy and δ_1 is the coefficient of interest. Just like the time series regressions earlier, I include a dummy for time period before October 2016 and for time period after April 2017 to estimate the effect from the months close to demonetization. I interact these dummy variables as well as the time trend and any controls with the GroupS dummy.

5 Results

This section presents the main results of the paper. First, I show results for household consumption, both durable and non-durable. Even though both income and consumption are available, I use consumption as

the primary measure here since for developing countries in particular, consumption is better measured and is also considered a better measure of household well-being as compared to income (Deaton (1997)). Also, as mentioned earlier, demonetization can also affect consumption for those households who do not experience an income shock. Then, I show the results for household borrowing. I follow this by results on income. This is followed by the results on heterogeneity of credit for farmers. After that, I show the results for a very specific sub-sample where one member of the household lost employment after demonetization. For each set of results, I first show the graphical results and then the regression estimates.

5.1 Purchase of durable assets

Here, I show evidence that demonetization led to a decline in the probability of purchasing a durable asset. As mentioned earlier, for durable goods, I do not see the actual expenditure in the data. I observe only whether or not the household purchased a durable good in the previous four months from the date of survey. The durable goods in the data include house, refrigerator, air conditioner, cooler, washing machine, TV, computer, car, two wheeler, inverter, tractor and cattle. For this analysis, I combine them all to create one dummy variable which indicates whether the household purchased any of the above assets in the previous four months. I also show evidence that the decline in the probability of purchasing a durable good is higher for relatively richer households as compared to the relatively poorer households.

Figure 2 shows the estimated time series for the probability of purchasing any durable asset in the previous four months after controlling for household fixed effects.[17] The base month for estimating the time series is October 2016. The y-axis shows the estimated proportion of households who said that they bought any of the durable assets in the previous four months and the x-axis shows the month of interview.[18] The month variable shows the year followed by the month number. For example, 2015m7 refers to the 7th month of 2015, that is, July of 2015. The figure shows the decline in the probability of buying the durable asset after demonetization. Also note that the decline would not show up right after October 2016 here as the question asks about the purchase of durable goods in the *four months prior to the date of survey*. For example, in December of 2016, a household is asked about the purchase of these assets in the months of August, September, October and November which include three months before demonetization as well in which people were not cash-constrained. Therefore, the decline shows up only a couple of months after demonetization.[19] The light grey lines show the

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[17]For estimating the time series of purchasing durable assets, I do not control for the number of assets that the household owns because then, the assets purchased would also affect the number of assets owned on the right hand side.

[18]The graph showing the average probability of purchasing any durable good, without controlling for household fixed effects is available in appendix figure A.10.

[19]Interestingly, the durable consumption does not pick up even some months after demonetization. I verify this pattern from the Index of Industrial Production (IIP) data from Ministry of Statistics and Program Implementation (MOSPI) which shows that the growth rates have been negative in 2017. The graph is available in the Data Appendix. Another verification exercise I do for the increasing pattern before 2016 is that I confirm that the increase in probability of purchasing washing machine and air conditioner is not increasing for households who do not have electricity access. While the IIP helps in the verification of the pattern towards the end of 2017, it still does not explain the reason durable

estimation window that I use for the regressions.

The regression results based on the estimated series are given in Table 2. The dependent variable is the dummy variable for whether the household purchased any of the durable assets in the past four months. The post-demonetization variable takes value 1 for months after December 2016. I take this cutoff as December for the regression for durable assets only to account for the question being asked about the previous four months. Using the period after December 2016 as post-demonetization ensures that there are at least two months after demonetization in the reference period when the question is asked. Note here that the number of observations for the regression is 46 as I use the data aggregated at month level for regression. The table also shows the number of raw observations used to estimate the monthly time series after accounting for household characteristics. The coefficient in column 1 shows that there is a statistically significant decline of around 4.4 percentage points in the probability of the purchase of durable goods after demonetization. The average probability of purchasing a durable asset in the pre-demonetization period is 5.9 percent and the average probability is close to 10 percent during six months before demonetization, which shows that the probability of purchasing durable good became nearly half of what it was in the six months before demonetization.

Columns 2 and 3 show the results separately for rural and urban households respectively. I break down the results by rural and urban areas as the low access to banking services and digital payments in rural areas may lead to a higher decline in these areas. In fact, we see that there is a higher decline in the probability of purchasing durable goods in urban areas. Even in proportional terms, this decline is higher for urban areas as compared to rural areas. This higher decline in urban areas could be there if both rural and urban households reduced their durable consumption to a similar low level which shows up as a higher decline for households with a higher baseline probability of durable purchases. The results in table 2 are based on the bandwidth of twelve months, that is, six months on either side of demonetization. However, the main result is not affected by this choice of bandwidth. The coefficient is pretty stable as I use different bandwidths- though as expected, the confidence intervals become larger at smaller bandwidths. The result is shown in appendix figure A.11.

To test for heterogeneity in effect by the nature of the occupation, I compare households with household head in the formal occupations to those households with the household head in the informal occupations. Here, I define formal occupations as comprising of businessmen, industrial workers, managers, self-employed professionals and entrepreneurs, and all the white-collar occupations. Similarly, informal occupations include farmers, agricultural laborers, wage laborers, and small traders. Figure 3a shows the probability of the purchase of durable goods for formal and informal workers. The figure shows a decline for both workers, indicating that the effect on the purchase of durable goods purchase was not limited to informal workers only. Panel A of Table 3 tests for a differential change in the probability of buying durable asset for formal and informal occupations. This regression is obtained by first, creating two time series from the household data, one for

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consumption does not pick up even after the liquidity is restored which is something that should be explored in further research.

the formal workers and the other one for the informal workers. I use these time series as dependent variables and include a dummy for formal workers and interact this dummy with all the other dummy variables. The number of observations used in the regression is thus 92, which comprises of 46 monthly observations for the two groups. Post*Formal shows the differential change of formal workers after the shock as compared to the informal workers. The interaction coefficient is -0.0165 which shows interestingly that the probability of buying durable assets for formal sector fell by 1.6 percentage points *more* as compared to the informal sector. However, the coefficient is not statistically significant and I cannot reject that the coefficient is 0 in this case.

To test for heterogeneity in effect by the economic well-being of the households, I compare households with below and above the median of the average household non-durable expenditure before demonetization. Figure 3b shows the probability of purchasing durable good in the previous four months for below and above median expenditure households and we can see that there is a decline in the probability after demonetization for both types of households. Panel B of Table 3 tests for a differential change in the probability of buying a durable asset by pre-demonetization expenditure. The interaction coefficient of -0.0335 indicates that the durable consumption actually fell by 3 percentage points *more* for those households who are above the median expenditure in the pre-demonetization period. Comparing to the baseline probabilities of the two groups, the decline is approximately *17% higher* for above-median expenditure households. A relatively higher decline, both in absolute and proportional terms, in durable consumption for richer households could be there if both kinds of households struggled to buy durable goods due to cash constraints and reduced their durable consumption to a similar low level which shows up as a higher decline for households with a higher baseline probability of durable purchases. We can see in the figure 3b as well that the probability of purchasing durable asset for both groups is very close to each other after demonetization. Another reason could be that due to an already higher durable consumption level, the additional purchases that the relatively richer households did not make during this period were mostly luxury purchases which they could afford to postpone. Thus, the relatively richer households could reduce durable consumption at a higher rate at a relatively lower cost as compared to the poorer households.

5.2   Non-durable consumption expenditure

Here, I provide results for the non-durable consumption expenditure. This includes the expenditure on food, clothing and footwear, education, health, various services including transportation and communication. The actual amount spent in rupees is available for the non-durable consumption. In this sub-section, I show that there was a decline in non-durable expenditure after demonetization and the amount of decline was higher for relatively richer households.

Figure 4 provides the estimated time series of the monthly average non-durable expenditure after controlling for household assets and household fixed effects. The base month is October 2016 and every other month's

expenditure is relative to that of October 2016.[20] The black dotted line is for October 2016. As we can see in the figure, there is a slight dip in the expenditure in months just after demonetization which I test further whether it is statistically significant or not. The increase in total expenditure that we see from mid-2015 has been mentioned in the Indian Economic Survey[21] as well and the decline in oil prices has been given as the main reason for this increase. To account for that pattern, I show that the results are robust to controlling for global oil price in the regression. The increase that we see in the second half of 2017, is coming from increase in consumption of clothing and footwear and various services and the Private Final Consumption Expenditure (PFCE) data collected by the Ministry of Statistics and Program Implementation (MOSPI) also shows high growth rates in consumption of clothing and footwear and services including transport, recreation, electricity, gas and fuels among others for the period 2017-18. The PFCE graphs are presented in the Data Appendix.

I use this estimated series as dependent variable in the second step to estimate the effect of demonetization by estimating equation 1. In particular, I control for the calendar month fixed effects and linear time trend for consumption changing over time. Also, to estimate the effect of demonetization from a 12-month window around the shock, I add dummies for period six months before the shock and six months after the shock and that period is depicted by the light grey lines in the figure 4. We can see that the increasing pattern towards the end would not affect the estimate as that is outside the estimation window.

Table 4 shows the statistical test for the decline in total expenditure. We can see in column 1 that the coefficient for the post demonetization dummy is -834 which indicates that the nominal expenditure fell by around 834 rupees after demonetization. The magnitude of the decline is roughly 10% of the average monthly household expenditure in the pre-demonetization period. Columns 2 and 3 show the results for rural and urban areas respectively. We can see that while the decline is there for both rural and urban areas, it is slightly higher for urban areas. The coefficient does not change much for different bandwidths around the shock. The result is also similar if instead of using nominal expenditure, I adjust the expenditure for Consumer Price Index (CPI) in the economy. These results are provided in appendix figures A.13a and A.13b. The regression results show that there was indeed a decline in non-durable consumption expenditure after demonetization, and as we can see from the figures, the decline seems to be happening in the initial months after demonetization.[22]

Figure 5a shows the expenditure by the formal and informal occupation of the household head. As we can see in the figure, the households with household head employed in the formal sector have higher expenditure

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[20]The graph showing the average non-durable expenditure without controlling for household fixed effects and household assets in available in Appendix figure A.12.

[21]Indian Economic Survey is an annual document presented by Department of Economic Affairs, Ministry of Finance which reviews the developments in the Indian economy over the past financial year, summarizes the performance on major development programs, and highlights the policy initiatives of the government and the prospects of the economy in the short to medium term.

[22]Since the pattern of increase from mid-2015 has been claimed to be there due to changes in oil prices, appendix table A.4 provides the expenditure regression after controlling for oil price in the US and its square. While both the variables show statistical significant relationship with the total expenditure, the post-demonetization coefficient still shows a decline in total expenditure and the magnitude is now even larger.

as compared to households with the household head employed in the informal sector. From the figure, it seems that both the groups show some decline in total expenditure but it's hard to say clearly which group shows a higher decline. Column 1 of Panel A of Table 5 formally tests for the change in expenditure for formal and informal occupations. As we can see, the expenditure actually seems to be falling *more* for the households whose household head is employed in the formal sector as compared to the informal households- with the estimate on the interaction being -477. However, since the households in formal occupation have higher level of non-durable expenditure before the shock, it is possible that the decline for formal and informal households is similar in proportional terms. Thus, column 2 presents results for log of expenditure. The coefficient on the interaction is -0.0197 which shows that the formal households experienced approximately *1.9% higher decline* in non-durable expenditure as compared to the informal households. However, the coefficient is not statistically significant and I cannot reject that the decline is the same in proportional terms for formal and informal sector households.

Figure 5b shows the heterogeneity based on the quintiles of the average non-durable expenditure in the period before demonetization. Here, we can see that there does not seem to be a graphical evidence of a decline in expenditure for the bottom quintiles while the topmost quintile seems to show some decline in the non-durable expenditure after demonetization. Column 1 of Panel B of Table 5 provides a formal test for the expenditure based on being below or above the median in the pre-demoneization expenditure. The interaction coefficient is -1230 which indicates that the expenditure for above median expenditure households fell by 1230 rupees *more* as compared to those below the median. Column 2 of the table shows the results in percentage terms by taking log of expenditure as the dependent variable. The coefficient is -0.0910 which shows that the above median expenditure households experienced approximately *9% higher decline* in non-durable expenditure as compared to the below median expenditure households. Therefore, even in proportional terms, the decline is higher for relatively richer households.

The result suggests that since relatively poorer households already have lower level of consumption, they could not reduce the expenditure without incurring high utility costs and therefore, tried to smooth their consumption using one mechanism or the other. On the other hand, the relatively richer households have higher level of consumption, reducing their expenditure by some amount for a small period of time did not involve high utility costs and therefore, they reduced their expenditure more as compared to relatively poorer households.

To test this result further, Figure 6a shows the regression coefficient based on the quintiles of the average pre-demonetization expenditure, with quintile 1 indicating bottom 20% of the households and quintile 5 indicating households in the top 20% of the expenditure distribution. As we can see from the figure, the maximum impact is there for the households belonging to the 5th quintile or the richest households based on the expenditure before November 2016. To account for the difference in levels, figure 6b shows the same results based on log of expenditure. We can see that in percentage terms too, the effect is the highest for the quintile 5 households and the lowest for quintile 1 households. In the next subsection, I show evidence that the poorer households used

higher credit to deal with the shock as compared to the richer households which further suggests that due to a high cost of reducing consumption, relatively poorer households relied more on coping mechanisms to smooth their consumption as compared to relatively richer households.

Among the categories of consumption, the maximum decline seems to be there for food, followed by clothing & footwear and education expenditure. These results are available in appendix table A.5. The decline in education expenditure could indicate that some households did not pay the school fees of the children in the months when they were cash-constrained but potentially made the payments later. Clothing and footwear have higher durability and thus, are goods whose purchases can be postponed. The decline in food expenditure, particularly since the maximum decline is coming from the richest households, indicates that if the richer households were buying food items in bulk earlier, they potentially bought only the necessary amount during the cash-crunch. Among food items, the maximum decline occurs for grains which are not very perishable and it is possible that the richer households purchase grains in bulk as they can be stored for a longer time.

5.2.1 Controlling for time trends

Since I am using the time series method for estimation of the effect of demonetization, the choice of time trend function is important as that function determines the counterfactual in this case. The baseline specification assumes a linear time trend and here, I show robustness to controlling for time trends more flexibly, that is, in a non-parametric way. The non-parametric time trend can also account for the increasing pattern that we see in the second half of 2017. First, I show the lowess plot (predicted values from locally weighted regressions) and the residuals for different bandwidths and then, I show the regression estimates from Robinson's partial linear model (Robinson (1988)).

Figure 7a shows the lowess fit for non-durable consumption expenditure as a function of time for the bandwidth of 0.8, that is, it uses 80% of the data for calculating the smoothed values for each point in the data. This specification does not control for any other variables and just plots the estimated expenditure time series as a function of time. Figure 7b shows the predicted residuals from this specification, that is, the time series of expenditure minus the values predicted by the lowess fit. We can see that the lowess fit with a high bandwidth captures only the broader trend and does not fit the data well. The predicted residuals show the decline after October 2016 in the estimated time series using this specification. Figure 7c, on the other hand, shows the lowess fit based on the bandwidth of 0.1. We can see that the lowess curve in this case fits the data better, but the time trend also captures almost all the month to month changes in the data, including any effect of the policy and therefore, we don't see the decline in the predicted residuals from this fit in the figure 7d after demonetization.

Thus, to fit the data well and to also see the effect of the policy, I need to select a bandwidth which is not very high and not very low. Therefore, I work with the bandwidth of 0.5. Figure 7e shows the lowess

plot from a bandwidth of 0.5 and figure 7f shows the corresponding predicted residuals. We can see from this plot that even after controlling for the time trend in this way, we see the decline after demonetization.[23] The regression coefficient also does not change much when I use the Robinson's semi-parametric approach (partial linear model). The results are given in appendix figure A.15.

Thus, the non-durable consumption expenditure estimate does not seem sensitive to the choice of time trend. Similarly, to test the sensitivity to the main heterogeneity test result, figures 8a and 8b show the predicted residuals after taking out the lowess time trend (with bandwidth 0.5) for expenditure quintiles one and five based on the pre-demonetization expenditure. Here also, we can see that, after taking out the lowess time trend, we see a decline in the residuals after demonetization mainly for the richest households (expenditure quintile 5) and not much for the poorest households (expenditure quintile 1).

5.3   Coping with the shock- credit

While we see a decline in consumption- both durable and non-durable, we actually see a more substantial decline for relatively richer households. This result suggests that households, especially relatively poorer households used some mechanism to deal with the shock. Households could have potentially borrowed in the smaller denomination notes. Also, it is possible that as the limited supply of the new currency was being rolled out, some people may have been able to lend in the new currency. In this sub-section, I show evidence that households increased borrowing, particularly from the local money lenders, to deal with the shock. The increase in the probability of having outstanding debt is the highest for relatively poorer households and households are borrowing the most for consumption purpose. These results imply that the relatively poorer households relied more on credit to maintain their consumption expenditure as they potentially had a higher cost to reducing their consumption, while we see a higher reduction in expenditure for the relatively richer households due to a potentially lower cost of reducing consumption.

As mentioned earlier, the borrowing data is available only in terms of binary variables. I only observe whether the household has any outstanding borrowing from a particular source for a particular purpose. I first show results for having any borrowing from any source. Figure 9 shows the probability of having any outstanding borrowing from any source for any purpose. The y-axis shows the proportion of households who report that they have an outstanding borrowing as of the date of the survey. As we can see, even though there is an increasing trend in the probability of having an outstanding borrowing, there seems to be a jump in the probability of borrowing right after October 2016, suggesting that borrowing went up right after demonetization. The figure shows a jump of roughly 5 percentage points from the average of 8-9 percent borrowing in the pre-

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[23]Appendix figure A.14a shows the lowess plot after adjusting for other controls in the time series regression, that is, a dummy for period six months before the shock, dummy for period six months after the shock and calendar month fixed effects. Similarly, appendix figure A.14b shows the corresponding residuals and the residuals from this specification also show the decline after demonetization.

demonetization period.[24] I focus on the various sources of borrowing to explore where people are borrowing from. I focus on the three most common sources of borrowing in the data- borrowing from money lenders, borrowing from banks and borrowing from friends and relatives.

Figure 10a shows the probability of borrowing from money lender for any purpose. The y-axis shows the proportion of households who reported that they had an outstanding borrowing from the money lender. Here also, we see an increasing trend but the figure also shows a jump of roughly 2-3 percentage points right after October 2016. Figure 10b shows the probability of having outstanding borrowing from a bank. The probability of having a bank loan also shows an increase of roughly 1 percentage point. Similarly, we can see in Figure 10c that borrowing from friends and relatives also jumps slightly after demonetization.

Table 6 shows the linear probability regression results for borrowing. Column 1 shows the result for any borrowing. Column 2 shows the results for borrowing from money lender, column 3 for bank borrowing and column 4 for borrowing from friends and relatives. The table shows that the probability of having any borrowing goes up after demonetization by around 2.1 percentage points. This is roughly 28% of the average probability of having any borrowing (7.5%) in the pre-demonetization period. We can see that there is no statistically significant change in borrowing from friends and relatives. There is a statistically significant increase in borrowing from money lenders and borrowing from banks which naturally shows up in the increase in column 1. The highest increase in borrowing seems to be coming from the money lenders. While the money lenders may be lending in the new currency to the local people, they may also have higher number of small denomination notes, as they make a lot of idiosyncratic loans on a day-to-day basis.

Hereafter, I focus on the borrowing from money lenders to test the heterogeneity in borrowing. Figure 11 shows the probability of borrowing from money lender based on the average expenditure of the households before November 2016. We can see that the increase after October 2016 seems to be a lot *higher* for the households below the median expenditure as compared to the households above the median. This figure suggests that the relatively poorer households had to rely *more* on local money lenders after the shock.[25] Table 7 shows the comparison for households below and above the median of the pre-period expenditure. We see that households below the median expenditure are borrowing by 2.8 percentage points *more* from money lenders as compared to the households above the median expenditure. In proportional terms too, the increase is higher for the households below the median expenditure.[26] These results imply that the relatively poorer households relied more on the money lender borrowing after the shock.[27]

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[24]The continuous increase in borrowing towards the end of 2017 has also been reported in newspapers which report that the household debt has almost doubled in 2017-18.

[25]Appendix figure A.17a shows the borrowing from money lenders for formal and informal occupations.

[26]The increase is 3.18 times the baseline probability for the below median expenditure households and 1.57 times the baseline probability for the above median expenditure households.

[27]Appendix table A.10 tests whether the relative increase in borrowing for households as shown in the above figures is statistically significant. The table shows the coefficient of an interaction between formal workers and the post-demonetization dummy. We see that the coefficient is -0.0144, implying that the increase in money lender borrowing is *less* for the formal sector workers by 1.4 percentage points. However, in proportional terms, the increase is higher

Just like for expenditure, Figure 12 shows the coefficient of the regression based on the expenditure in the pre-demonetization period. We see here that the maximum increase is borrowing is seen among households in the bottom of the distribution or the relatively poorer households while the richest households (quintile 5) show the least amount of increase in the probability of borrowing. This result further supports the claim that relatively poorer households used borrowing from money lender to support their consumption while the relatively richer households did not rely on money lender borrowing to deal with the shock.

To test the claim that the households borrowed from money lenders after demonetization to support their consumption, here, I provide results for the stated purpose of borrowing. It might be hard for the household to report one specific purpose of the borrowing as the borrowed money may be used towards various objectives, however, it is still informative about the reason households are borrowing for. The data provides binary variables on the purpose of borrowing as well. Table 8 reports the results for different reasons for borrowing. We see that while households are increasing borrowing for different reasons, the highest increase is there for consumption purpose. This result further implies that borrowing was used to maintain the household consumption during the shock.

5.4 Household income

The decline in consumption that we see after demonetization can happen in two ways: one is through the impact on income, that is, a decline in income leading to a decline in consumption as well, and second is directly due to the liquidity constraints and the inability of the households to have the requisite currency for their day-to-day purchases. To test how much of this effect is through the effect on income, in this sub-section, I show the results on income. In particular, I show that I cannot reject that there is no impact on household income and I do not see a differential impact on income for relatively richer and poorer households. For this analysis, I focus on total household income obtained from all sources. Figure 13 shows the estimated time series for household income. The base month is October 2016 and all other coefficients are relative to October 2016 income. As we can see, there is some seasonality in the income data but there does not seem to be any evidence of a decline in household income after demonetization. There is also an increasing pattern in income towards the latter half of 2017. While the pattern is not a part of the estimation window and thus, would not affect the estimate, I also show the robustness of the estimate to controlling for this trend more flexibly and in the data appendix, I discuss the potential reasons for this increase in the data. Table 9 shows the estimated coefficient for the post-demonetization dummy based on the time series.. The coefficient is 492.7 and is not statistically different from 0. Therefore, we do not see any evidence of a decline in income after demonetization in this specification. Columns 2 and 3 show the results for rural and urban areas separately. For both rural and urban areas, the

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for households with household head employed in the formal sector as the baseline probability of borrowing from money lender is lower for these households.

coefficients are actually positive and we do not see evidence of a decline in income.

The above result is based on a 12-month window around demonetization. To make sure the results are not affected by the selection of bandwidth, Figure 14a shows the coefficient for different bandwidths. The y-axis shows the number of months in the window. As we can see, for each specification, we cannot reject that the coefficient is equal to 0. However, we also see that the coefficient is becoming more negative as the bandwidth is becoming smaller. With smaller bandwidth, the variance increases but the bias actually reduces. Therefore, while we cannot reject that the estimate is 0, a negative estimate in the four-month and six-month window suggests a possible negative impact on household income in the initial one or two months after demonetization. Taking the 95% confidence interval of the eight-month window, which provides a balance between bias and variance, we can rule out a negative impact on household income greater than 750 rupees or about 5% of the baseline average household income before demonetization.

To test if the patterns in consumption and borrowing are due to a differential impact on income for these quintiles, I generate the plot for income effects based on the same expenditure quintiles. Figure 14b shows that there does not seem to be evidence of a differential effect on household income for different expenditure quintiles. Hence, the pattern in non-durable expenditure and borrowing do not seem to be driven by the impact on income and are instead driven by the lack of requisite currency for the day-to-day purchases. One way this could be possible is that if the households received deferred payments for their earnings due to the cash-crunch, they may not report a decline in income but they may not have the valid currency in hand to make the purchases.[28]

Just like the non-durable consumption expenditure, we also see an increasing trend in household income in the second half of 2017. To make sure the results are not affected by the choice of time trend, I test the robustness by fitting the time trend flexibly with a bandwidth of 0.5. The results are not sensitive to the choice of time trend function and in the semi-parametric model also, the effect is very close to zero. Figures are shown in the appendix.

5.5   Heterogeneity in credit based on cash reliance

In the previous section, I showed that the probability of having outstanding borrowing increased after demonetization. In this section, to show that borrowing was a result of being cash constrained, I focus on farmers to show that the use of credit was higher among households who rely more on cash. Among farmers, those who consume their own grown food presumably deal less in cash because they need to make fewer purchases from the market as compared to those farmers who do not consume their own grown food. So, if the use of credit after demonetization was a result of being cash constrained, credit should go up less for those farmers

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[28]Another potential reason could be the shortage of smaller denomination currency notes. In the beginning, only the new 2000 rupees notes were being rolled out and the new 500 rupees notes started rolling out much later, as a result of which, people had the 2000 rupees notes but were finding it hard to spend them because many people did not have the required change in the smaller denomination currency notes.

who consume their own grown food in comparison to those farmers who don't. To do this analysis, I keep only those households whose head of the household is a farmer, which leaves me with 44,741 households. I focus on farmers for this analysis as apart from being a relatively un-banked population which relies a lot on cash, farmers provide this natural categorization on use of cash based on whether they consume their own grown food or not.

To define farmers who consume their own grown food, I use data on household imputed income. I assume that for farmers, all the imputed income is from own grown food consumed at home. I create the proportion of imputed income out of food expenditure. In my primary specification, I take annual food expenditure and annual imputed income. For roughly 60% of the observations, this proportion is equal to 0. The 99th percentile value is 0.93.[29] This proportion is 0 for close to 50% of the observations based on the total food expenditure in *all the periods* and total imputed income in *all the periods*. Based on the above proportions yearly, I define households with value of this proportion greater than 0 as own grown food consumers. I call them 'Subsistence households'. I define those with the proportion value equal to 0 as those who do not consume own grown food. I call them 'Non-subsistence households'.[30] [31]

I focus primarily on borrowing from money lenders, which showed the maximum increase in borrowing in the previous section. Money lenders are also likely to be the relevant source for farmers who want to borrow money to deal with the shock. Figure 15 shows the probability of borrowing from money lender for subsistence and non-subsistence households based on the annual definition. As we can see in the figure, the borrowing probability is very similar for both groups of households before demonetization, but after demonetization, while the borrowing probability increases for both sets of households, the increase in probability is *higher* for non-subsistence households.

Now, I test statistically whether the difference in increase in the borrowing probability for the two groups of farmers is statistically significant. I do this analysis in a Difference-in-Difference framework and observe the differential change in borrowing after demonetization in the two groups. Note that this is not exactly a Difference in differences as the cross sectional variation here is not exogenous and a household being subsistence or non-subsistence is likely to be non-random. I use the same framework here as for other regressions. I estimate the time series of the variables for the two groups after controlling for household characteristics and then use the predicted time series as dependent variables.

Table 10 shows the results on borrowing from money lenders for subsistence and non-subsistence households. The results are based on the annual definition. The coefficient of interest is the coefficient on the interaction

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[29]The distribution of this proportion is shown in appendix figure A.21.

[30]I also use alternate definitions where I define the bottom 75% of the proportion as non-subsistence households for robustness.

[31]Note that the subsistence households, as I define them here, do not have imputed income as their only income. I call them subsistence and non-subsistence households only based on the proportion of their food expenditure coming out of the imputed income.

term of subsistence and post-demonetization dummy. As we can see, this coefficient shows that the probability of borrowing from money lender increased by around *4 percentage points less* for subsistence households as compared to non-subsistence households.

In Table 11, I test for robustness of the above result by taking various definitions of the subsistence household. Column 1 takes the definition of subsistence and non-subsistence households based on all periods of data. We can see that while the coefficient is slightly smaller than the one in Table 10, it is statistically significant and indicates that subsistence households borrowed less after demonetization as compared to the non-subsistence households. Similarly, column 2 shows the robustness result where based on the yearly data, I define the subsistence households as those who are in the top 25% of the proportion of imputed income out of the total food expenditure and again, the result does not change much.

Due to the shortage of cash, it might be the case that some non-subsistence farmers may have turned into subsistence farmers which can lead to bias in the estimates. To tackle this concern, I define subsistence households on the basis of food expenditure and imputed income in 2015, that is, the year before demonetization. This definition would not be affected by farmers changing subsistence status after demonetization. The results are given in column 3 and as we can see, the coefficient does not change much and indicates the same result that the subsistence households increased their borrowing by less as compared to the non-subsistence households.

It is possible that the difference we see in borrowing for the two groups of farmers might be because the subsistence households were not able to borrow rather than they not needing to borrow as much as the non-subsistence households. While the time series are estimated after controlling for household assets to proxy for their ability to borrow, another test would be to see if the consumption is changing differently for the two groups. If the subsistence households were not able to borrow after the shock while the non-subsistence households were, we should see that expenditure for non-subsistence households was not affected while that of subsistence households should at least be more affected as compared to that of non-subsistence households. Table 12 shows the result for the expenditure change after the shock. The coefficient of the interaction shows that the non-durable expenditure did not change differently for the two groups while the borrowing changes differently for the two groups. These results suggest that the change in borrowing that we observe between the two groups is not due to the inability of the subsistence households to borrow.

5.6   Effect on those who lost employment

There has been some evidence of loss in employment due to demonetization (Chodorow-Reich et al. (2020), CMIE (2018), State-Of-Working-India-Report (2019)), and if households suffering employment shock tend to rely on borrowing from money lender to deal with the shock, the effect on borrowing could be just coming from those households. To test if this is the case, I compare the effect on households where at least one member lost employment after demonetization to those households where at least one member lost employment during any

other point of time. Even though these sub-samples are very selected ones, they can be informative about the response of households to employment shock during demonetization as compared to other time and also the severity of the impact on households as a result of employment shock experienced during demonetization as compared to one experienced during other time.

For this analysis, for selecting households who experienced employment shock after demonetization, I restrict myself to those households where at least one household member who was employed in the three months before demonetization (that is, August, September and October 2016) reported being unemployed in the three months after demonetization (that is, December 2016, January and February 2017). For this analysis, I follow Chodorow-Reich et al. (2020) and drop households being interviewed in November to be able to better capture households who suffered employment shock as a result of demonetization. To get the comparison group suffering employment shock during other point of time, I take an arbitrary cutoff of April 2016[32] and select those households where at least one household member who was employed in the three months before April 2016 reported being unemployed in the three months after April 2016. The ideal comparison group would be those losing employment after November in an earlier year, say 2015. However, the employment data starts only from January 2016. Thus, to be able to capture three months before the shock, I take April 2016 as the corresponding cutoff for the comparison group.

Figure 16a shows the probability of borrowing from money lenders for those households where at least one household member lost employment after November 2016 while figure 16b shows the same result for households facing employment shock after April 2016. We see that the households losing employment after November show an increase in probability of borrowing from money lenders after the shock which is what we saw for the overall sample as well. But for the households losing employment after April, we do not see a corresponding increase in borrowing after the employment shock. The increase that we see later in this graph is actually coming after demonetization only. This result suggests that households do not seem to rely on money lender borrowing when faced with employment shock during other time. One explanation why households are not relying on borrowing after facing employment shock after April could be that the income and expenditure effect could be different of losing employment after April. Figures 16c and 16d show the income response of losing employment during the two periods and figures 16e and 16f show the non-durable consumption expenditure response for both sets of households. We can see that the income and expenditure responses are not very different in the two cases.

Table 13 shows the statistical test for these outcome variables and reports the coefficient on post-demonetization for each outcome variable. Row one shows the results for households losing employment after November while the second row shows the results for households facing employment shock after April 2016. We can see that while borrowing from the money lender shows an increase of 3 percentage points for those losing employment after demonetization, there is no such increase for households facing employment shock after April 2016.[33] Columns

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[32]Results are similar if I take the cutoff of July 2016 instead of April 2016.

[33]I find the same results for any source of borrowing as well, so these households do not seem to be borrowing from

2 and 3 present the results for income and non-durable consumption expenditure respectively. We can see that the income loss is actually larger for those losing employment after April 2016 but the expenditure response is very similar in the two cases and much less as compared to the income response for both households. This result suggests that households do not seem to rely on borrowing when they face an employment shock during other times and it is not because the severity of income shock is less in April 2016 and the fact that consumption loss is much less as compared to income loss shows that households potentially have other mechanisms to deal with the employment shock happening during other time. The result also shows that it is only due to the liquidity constraints imposed by demonetization that the households had to rely on the borrowing from money lender after November 2016 and it was not the loss in employment that made them borrow more.

6   Conclusion

The results in this paper provide evidence on national-level impact of demonetization. I find that while I do not reject demonetization having no impact on aggregate income, the durable and non-durable consumption were negatively affected by the shock. The effect is only there for a few months and then the consumption starts increasing again. Analyzing the heterogeneity by the average expenditure before November 2016, I find that households below the median expenditure actually experienced a smaller decline in household expenditure as compared to those above the median expenditure. But these relatively poorer households also relied more on informal borrowing to deal with the shock. The results suggest that since the relatively poorer households had a lower consumption level to begin with, they faced a higher cost in reducing their consumption and therefore, chose to pay the interest rates charged by money lenders to sustain their consumption. On the other hand, the relatively richer households faced a lower cost in reducing their consumption and could therefore, afford to reduce their consumption temporarily rather than paying the interest to maintain the same consumption level.

In terms of the policy, while this paper does not cover the benefits of the policy, the paper points to the short-term costs of the policy. Incurring more debt from the high interest rate money lenders and reducing the consumption temporarily led to a reduction in welfare for many households. My results also suggest that in the drive towards more formalization, it is the informal sector which helped people in dealing with the shock, and this drive may have further strengthened the informal networks in the country.

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any other source either.

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Figures

Figure 1: Currency in circulation
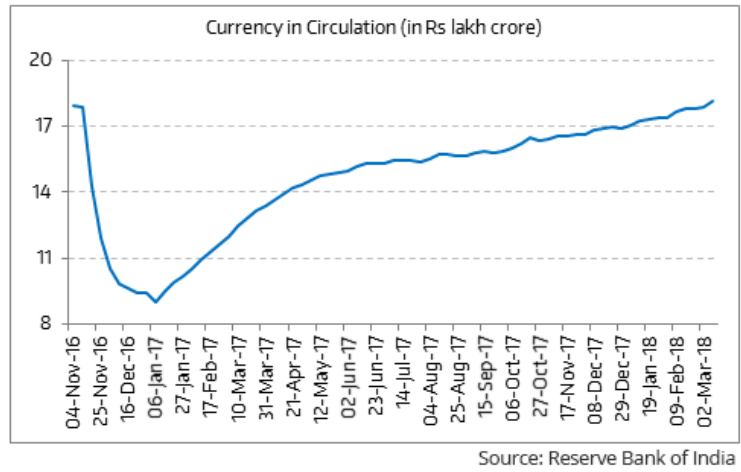
Figure 2: Probability of buying asset in the last 4 months
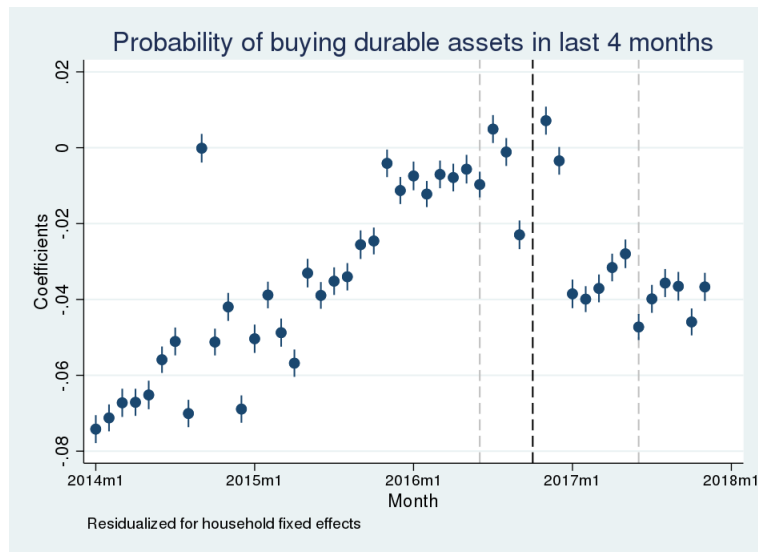
Figure 3: Probability of buying asset in the last 4 months: Heterogeneity

(a) By occupation
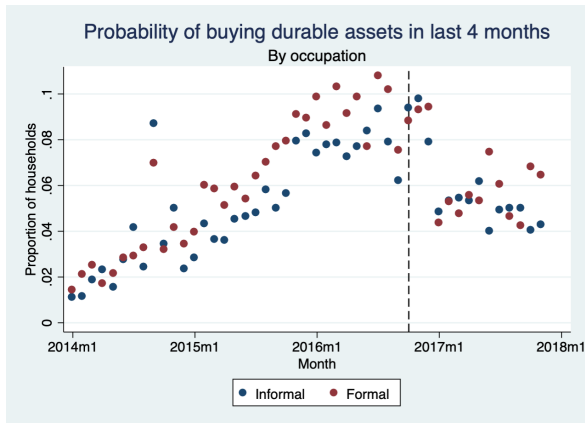
(b) By pre-demometization expenditure
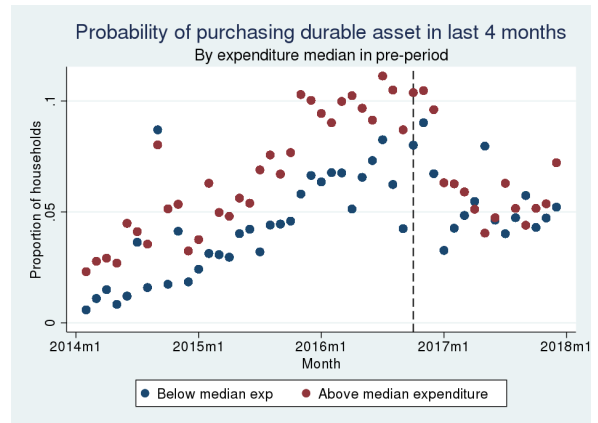
Figure 4: Estimated time series of non-durable expenditure
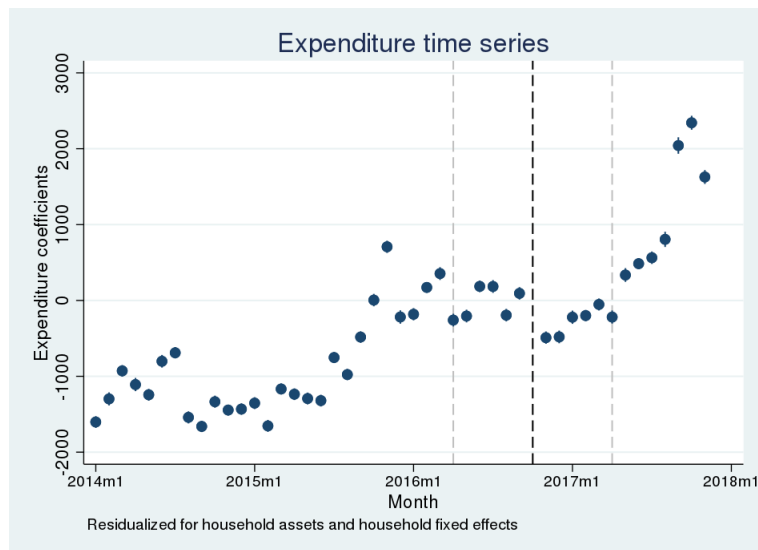
Figure 5: Average monthly expenditure: Heterogeneity

(a) By occupation
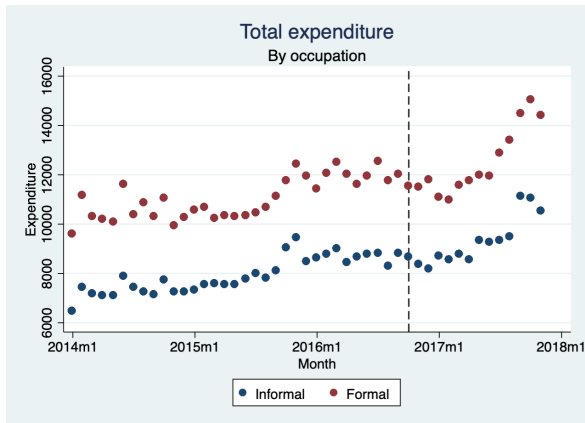
(b) By pre-demonetization expenditure
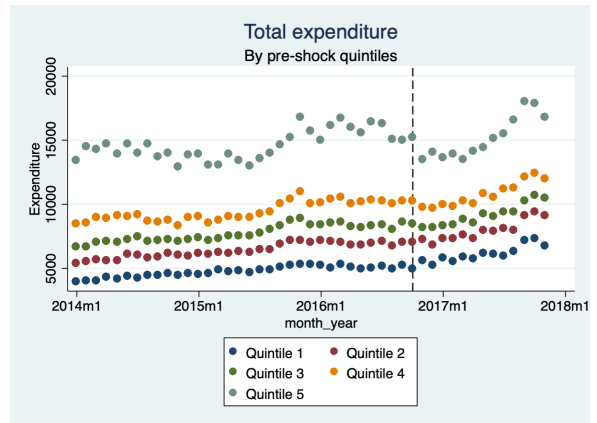
Figure 6: Coefficient of expenditure regression: By pre-period quintiles

(a) Expenditure
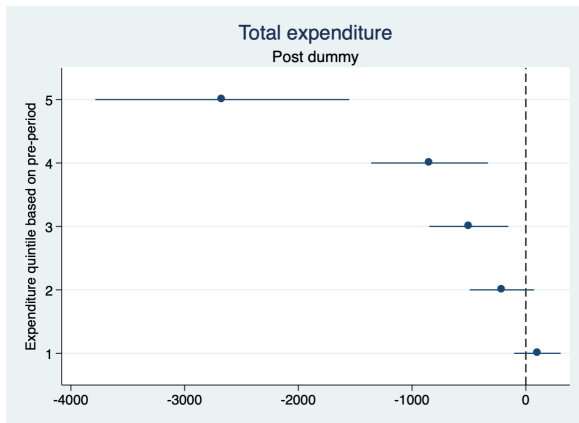
(b) Log expenditure
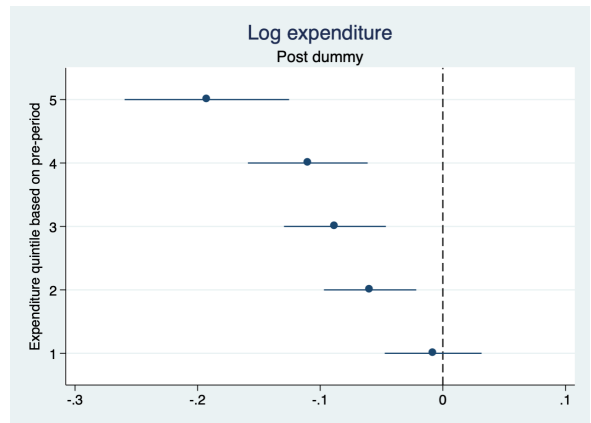
Figure 7: Lowess plot and predicted residuals of expenditure by different bandwidths

Bandwidth=0.8

(a) Lowess plot
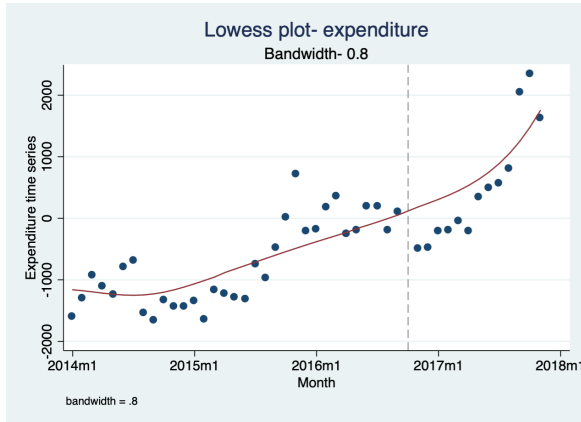
(b) Residuals
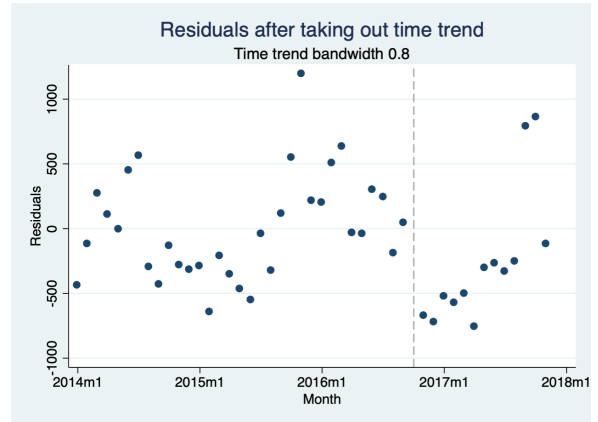
Bandwidth=0.1

(c) Lowess plot
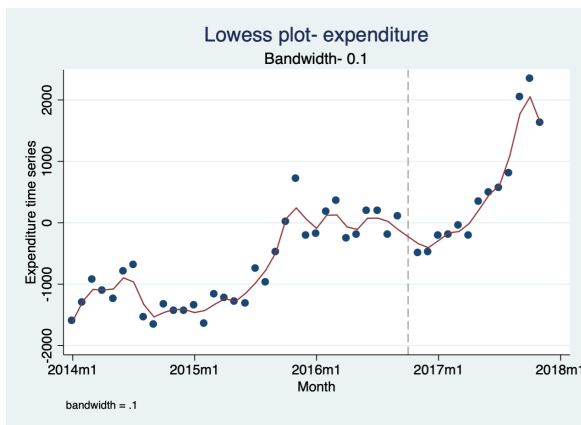
(d) Residuals
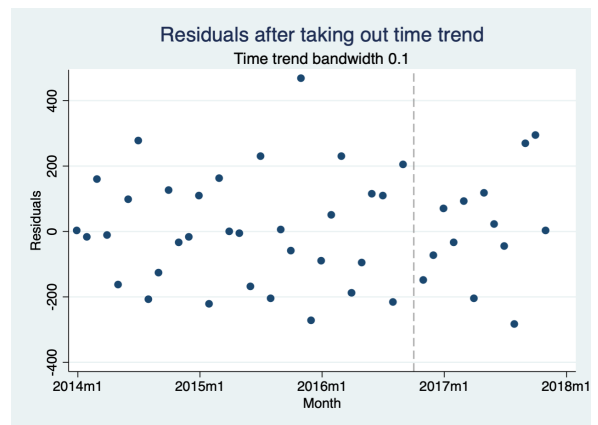
Bandwidth=0.5

(e) Lowess plot
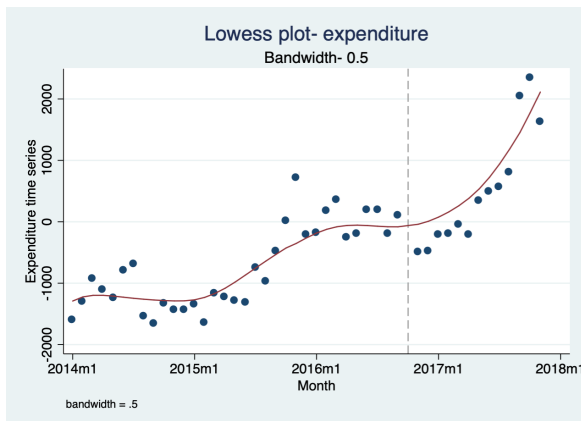
(f) Residuals
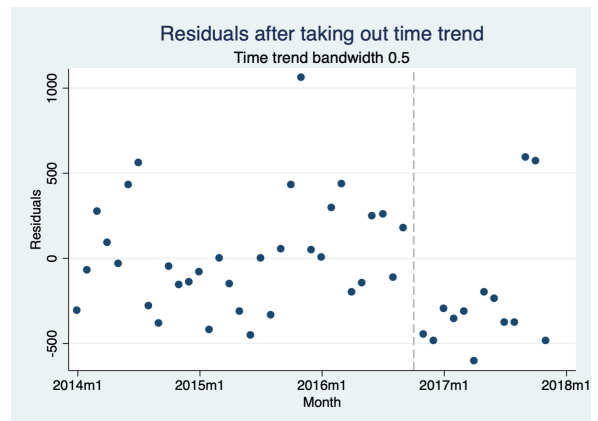
Figure 8: Predicted residuals: by expenditure quintiles

(a) Expenditure quintile 1
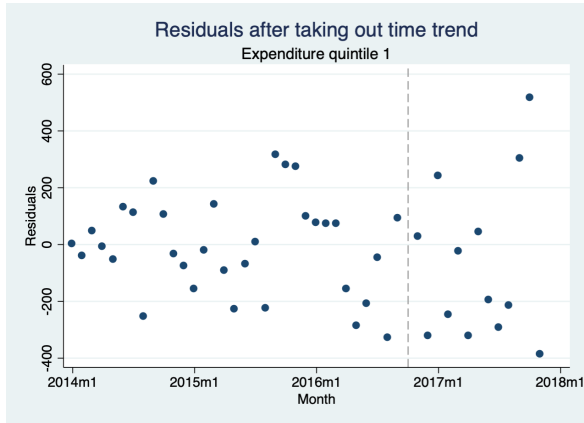
(b) Expenditure quintile 5
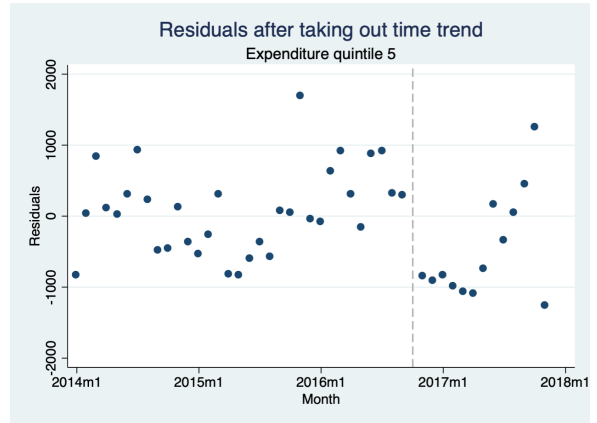
Figure 9: Probability of having a borrowing
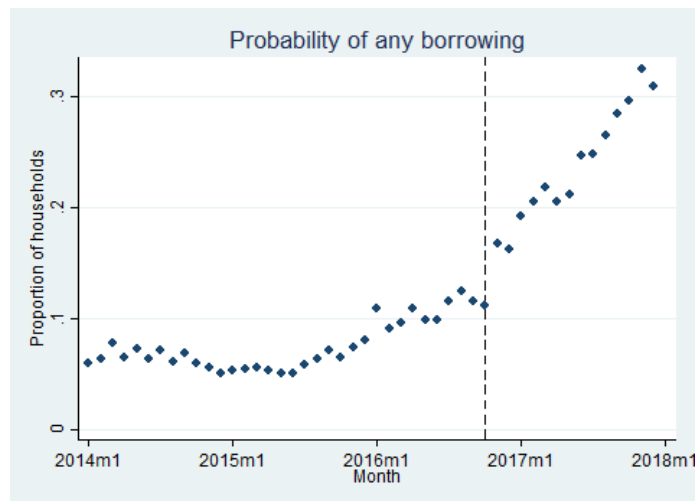
Figure 10: Probability of borrowing from different sources

(a) Money lender

(b) Bank
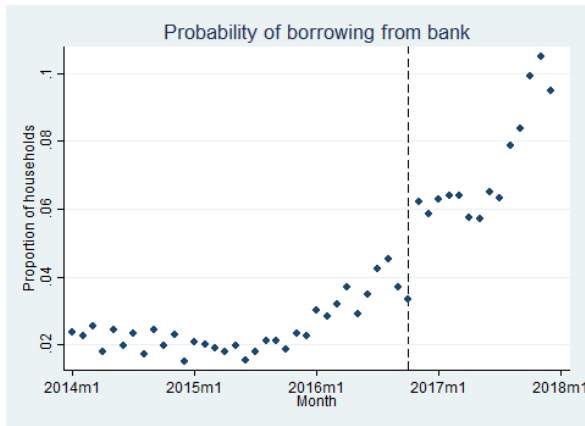
(c) Friends and relatives
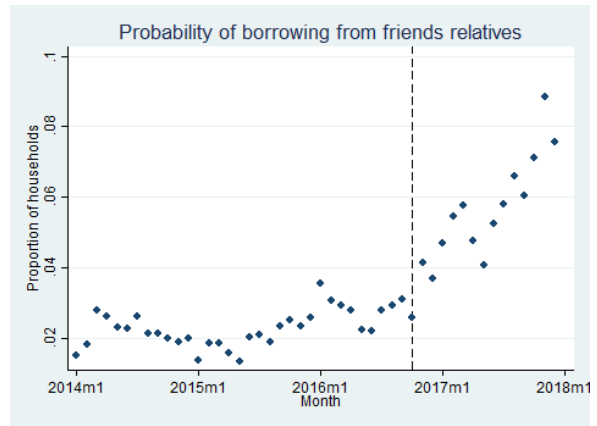
Figure 11: Probability of borrowing from money lender: By pre-period expenditure

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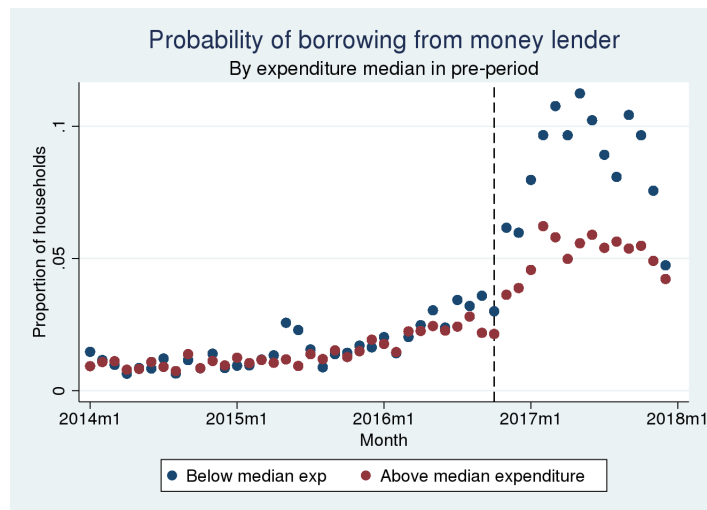
Figure 12: Coefficients of borrowing from money lender: By pre-period expenditure quintiles
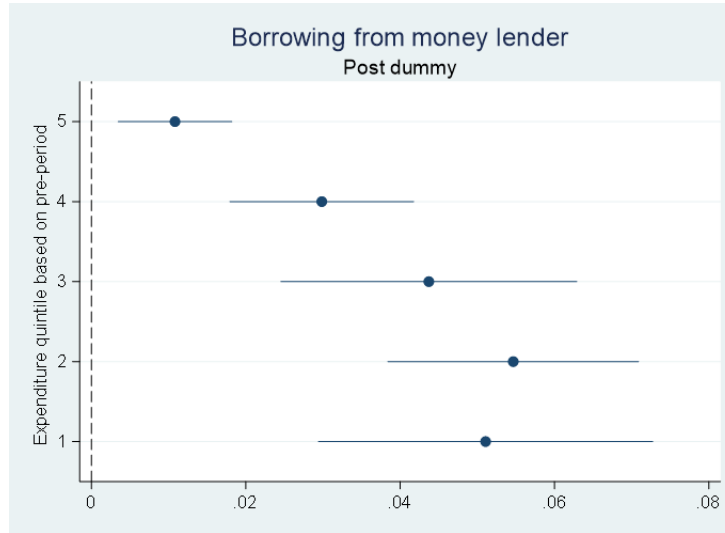
Figure 13: Average monthly income predicted time series
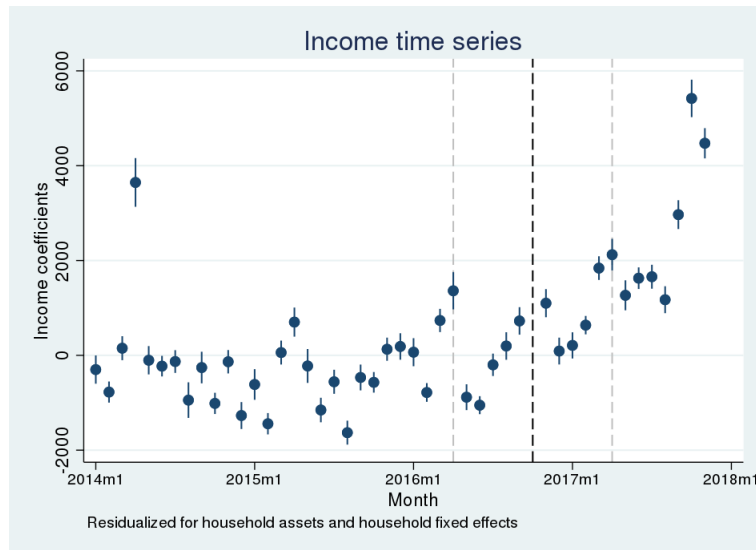
Figure 14: Income: Different Bandwidths and Heterogeneity

(a) Coefficients by different bandwidths: Income

(b) Coefficients by different quintiles of expenditure
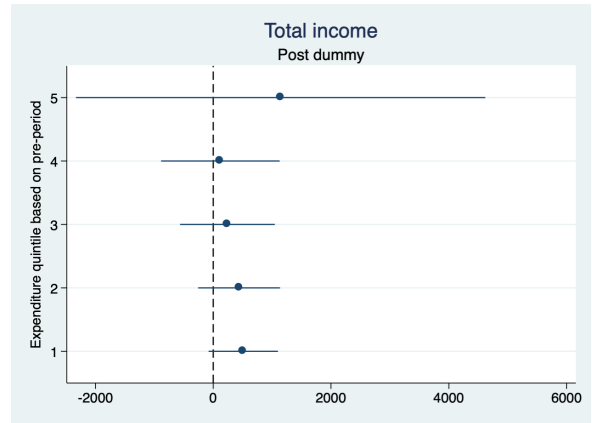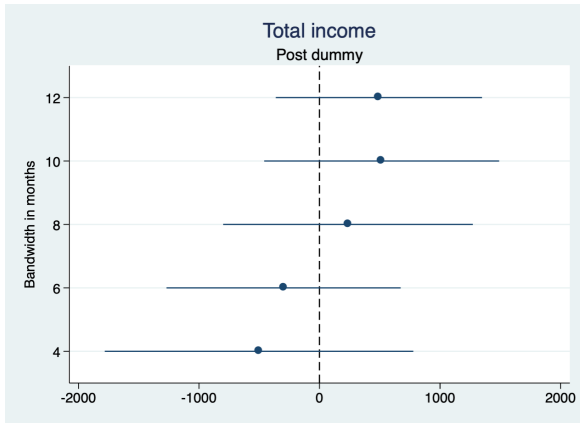
Figure 15: Probability of borrowing for subsistence and non-subsistence households: annual
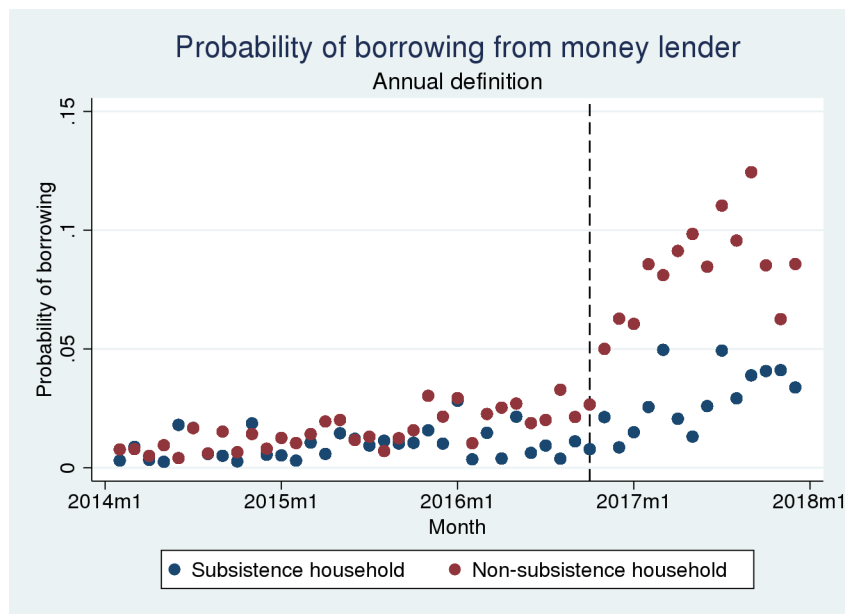
Figure 16: Results for those who lost employment

Panel A: Borrowing from money lender

(a) Lost employment after November
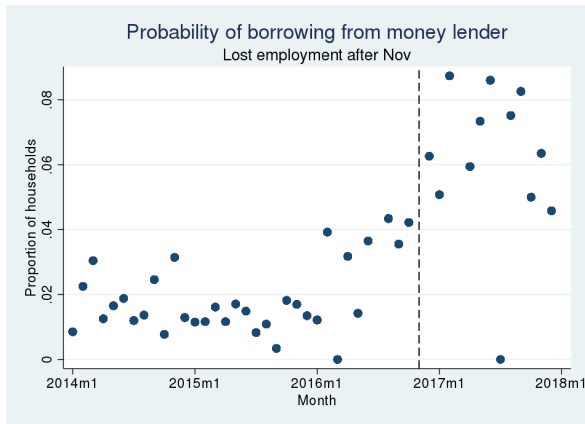
(b) Lost employment after April
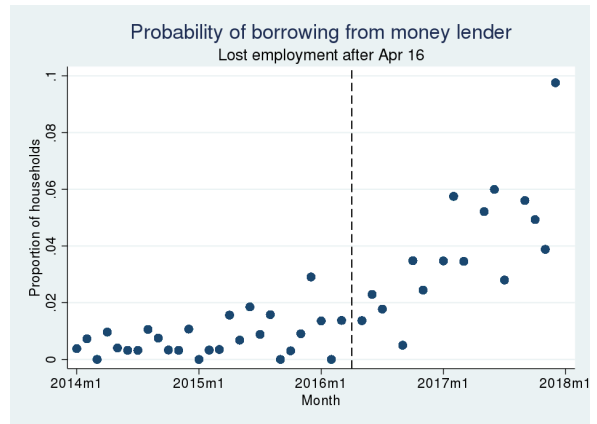
Panel B: Income

(c) Lost employment after November
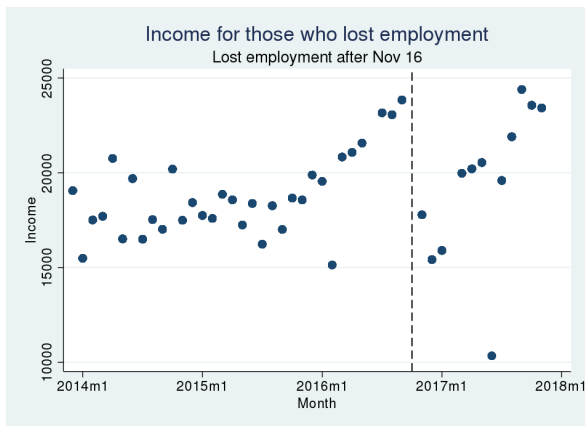
(d) Lost employment after April
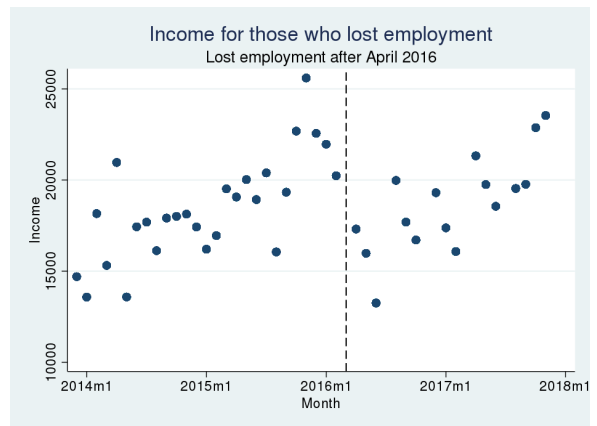
Panel C: Non-durable expenditure

(e) Lost employment after November

(f) Lost employment after April

Tables

Table 1: Summary statistics

	Rural		Urban	
	Pre	Post	Pre	Post
Total expenditure	7935.8	9401.6	10169.3	11313.5
	(5674.8)	(6552.5)	(7003.7)	(8982.9)
Per capita expenditure	2021.8	2510.9	2746.4	3263.4
	(1529.8)	(1957.9)	(2069.9)	(2649.5)
Food expenditure	4170.7	4496.6	4776.0	4955.2
	(1618.7)	(1920.4)	(1881.8)	(2208.5)
Education expenditure	255.9	317.3	428.5	482.4
	(1028.6)	(1196.3)	(1715.2)	(1577.5)
Health expenditure	160.3	257.0	206.5	305.9
	(1057.0)	(1917.8)	(1050.9)	(3289.3)
Clothing-footwear expenditure	394.1	503.3	502.9	617.1
	(1074.4)	(1600.2)	(1430.8)	(2224.2)
Power and fuel expenditure	1041.2	1267.4	1642.6	1842.1
	(901.1)	(998.7)	(1368.9)	(1470.5)
Total income	12068.5	14418.3	17804.0	20271.2
	(16388.2)	(46220.1)	(16394.2)	(59891.0)
Any outstanding borrowing	0.09	0.27	0.07	0.22
	(0.28)	(0.44)	(0.25)	(0.41)
Outstanding borrowing from money lender	0.02	0.07	0.01	0.06
	(0.13)	(0.26)	(0.12)	(0.23)
Outstanding borrowing from bank	0.03	0.08	0.02	0.07
	(0.16)	(0.27)	(0.15)	(0.25)
Outstanding borrowing from relatives friends	0.02	0.07	0.02	0.05
	(0.15)	(0.25)	(0.14)	(0.22)
Number of durable assets owned	3.71	3.87	4.74	4.89
	(1.88)	(1.91)	(2.24)	(2.15)
Bought durable asset in last 4 months	0.05	0.06	0.06	0.06
	(0.22)	(0.23)	(0.24)	(0.23)
Observations	351168	150219	807695	321379

The table provides the averages of the above variables before and after demonetization, separately for rural and urban areas.

Table 2: Buying durable assets by region

	(1) All	(2) Rural	(3) Urban
Post demonetization	-0.04***	-0.03***	-0.07***
	(0.01)	(0.01)	(0.01)
Observations	46	46	46
Raw observations	1596753	506417	1090336
Mean (Pre-Nov 16)	0.06	0.05	0.06

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is the estimated time series of probability of purchasing a durable asset in the 4 months prior to survey, after controlling for household fixed effects. The table shows the coefficient of the post December 2016 dummy variable (to account for the question being asked about the *previous 4 months*) in the time series regression. Other controls in the time series regression include calendar month dummies, linear time trend, a dummy for months before June 2016 and a dummy for months after June 2017 to estimate the coefficient from a window around demonetization. Column 1 shows the effect for all the households and columns 2 and 3 show the effect for rural and urban areas respectively

Table 3: Buying durable asset in last 4 months: Heterogeneity

	(1) Probability of buying durable good
Panel A	
Formal*post	-0.01
	(0.01)
Panel B	
Above med exp*post	-0.03**
	(0.01)
Observations	92
Raw observations	1528375

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel A, the dependent variable is the estimated time series of probability of purchase of durable assets in the 4 months prior to the survey, separately for formal and informal occupations, after controlling for household fixed effects. The table shows the coefficient of the interaction of formal occupation dummy and post December 2016 dummy variable in the time series regression. Other controls in the time series regression include formal occupation dummy, post December 2016 dummy, calendar month dummies to account for seasonality, linear time trend, a dummy for months before June 2016 and a dummy for months after June 2017 and interactions of the formal occupation dummy with the time trend and time dummy variables. Similarly, Panel B shows the coefficient of the interaction of Post dummy and Above median expenditure households based on pre-demonetization expenditure.

Table 4: Total expenditure by region

	(1) All	(2) Rural	(3) Urban
Post demonetization	-834.4***	-680.7***	-1118.2***
	(213.1)	(213.0)	(362.8)
Observations	46	46	46
Raw observations	1547996	476417	1071579
Mean (Pre-Nov 16, Rupees)	9052.5	7935.8	10169.3

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is the estimated non-durable expenditure time series after controlling for household wealth controls and household fixed effects. The table shows the coefficient of the post October 2016 dummy variable in the time series regression. Other controls in the time series regression include calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017. Column 1 shows the result for all the households while columns 2 and 3 show the results for rural and urban areas separately.

Table 5: Total expenditure: Heterogeneity

	(1) Expenditure	(2) Log expenditure
Panel A		
Formal*post	-477.5*	-0.02
	(249.4)	(0.02)
Panel B		
Above med exp*post	-1230.1***	-0.09***
	(215.3)	(0.02)
Observations	92	92
Raw observations	1527949	1527949

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

In panel A, the dependent variable is the estimated non-durable expenditure time series, separately for formal and informal occupations, after controlling for household wealth controls and household fixed effects. In column 1, the series is estimated for the non-durable expenditure and in the second column, the series is estimated for log of non-durable expenditure. The table shows the coefficient of the interaction of formal occupation dummy and post October 2016 dummy variable in the time series regression. Other controls in the time series regression include formal occupation dummy, post October 2016 dummy, calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 and interactions of the formal occupation dummy with the time trend and time dummy variables. Similarly, Panel B shows the coefficient of interaction of Post dummy and Above median expenditure households based on pre-demonetization expenditure.

Table 6: Probability of borrowing from different sources

	(1) Any source	(2) Money lender	(3) Bank	(4) Friends and relatives
Post demonetization	0.021***	0.018***	0.005**	-0.002
	(0.004)	(0.003)	(0.002)	(0.002)
Observations	46	46	46	46
Raw observations	1596753	1596753	1596753	1596753
Mean (Pre-Nov 16)	0.0756	0.015	0.025	0.023

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable in each column is the estimated time series of probability of having an outstanding borrowing after controlling for household wealth controls and household fixed effects, for any source, money lender, bank and friends and relatives respectively. The table shows the coefficient of the post October 2016 dummy variable in the time series regression. Other controls in the time series regression include calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 to estimate the coefficient from a window around demonetization.

Table 7: Borrowing from money lender by pre-demonetization expenditure

	(1) Probability of borrowing
Above med exp*post	-0.028***
	(0.007)
Observations	92
Raw observations	1528375

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is the estimated time series of probability of having an outstanding borrowing from money lender, separately for households below and above the median of the average household expenditure before November 2016, after controlling for household wealth controls and household fixed effects. The table shows the coefficient of the interaction of above median expenditure dummy and post October 2016 dummy variable in the time series regression. Other controls in the time series regression include above median expenditure dummy, post October 2016 dummy, calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 to estimate the coefficient from a window around demonetization and interactions of the above median expenditure dummy with the time trend and time dummy variables

Table 8: Purpose of borrowing

	(1) Consumption	(2) Durable consumption	(3) Business	(4) Marriage	(5) Medical
Post demonetization	0.029*** (0.006)	0.009*** (0.001)	0.002 (0.002)	0.004*** (0.001)	0.003*** (0.001)
Observations	46	46	46	46	46
Raw observations	1596753	1596753	1596753	1596753	1596753
Mean (Pre-Nov 16)	0.019	0.004	0.005	0.004	0.003

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable in each column is the estimated time series of probability of having an outstanding borrowing after controlling for household wealth controls and household fixed effects, separately for each purpose of borrowing. The table shows the coefficient of the post October 2016 dummy variable in the time series regression. Other controls in the time series regression include calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 to estimate the coefficient from a window around demonetization.

Table 9: Total income by region

	(1) All	(2) Rural	(3) Urban
Post demonetization	492.7 (418.9)	207.8 (566.3)	909.9 (547.9)
Observations	46	46	46
Raw observations	1547996	476417	1071579
Mean (Pre-Nov 16, Rupees)	14929.25	12068.5	17804.0

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is the estimated income time series after controlling for household wealth controls and household fixed effects. The table shows the coefficient of the post October 2016 dummy variable in the time series regression. Other controls in the time series regression include calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 to estimate the coefficient from a window around demonetization. Column 1 shows the result for all households while columns 2 and 3 show the coefficients for rural and urban areas respectively.

Table 10: Probability of having a borrowing from money lender by subsistence

	(1) Probability of borrowing from money lender
Subsistence*Post	-0.040***
	(0.009)
Observations	92
Raw observations	195942

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is the estimated time series of probability of having an outstanding borrowing from money lender after controlling for household wealth controls and household fixed effects, separately for subsistence and non-subsistence households. A subsistence household is defined as the one where the head of the household is a farmer and the ratio of annual imputed income to annual food expenditure is greater than 0. The table shows the coefficient of the interaction of subsistence household dummy and post October 2016 dummy variable in the time series regression. Other controls in the time series regression include subsistence household dummy, post October 2016 dummy, calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 to estimate the coefficient from a window around demonetization and interactions of the subsistence household dummy with the time trend and time dummy variables

Table 11: Probability of having a borrowing from money lender by subsistence

	(1) All periods	(2) Top 25%	(3) Based on 2015
Subsistence*Post	-0.023**	-0.028***	-0.022*
	(0.010)	(0.009)	(0.011)
Observations	92	92	92
Raw observations	195942	195942	155857

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is the estimated time series of probability of having an outstanding borrowing from money lender after controlling for household wealth controls and household fixed effects, separately for subsistence and non-subsistence households. Each column defines subsistence household differently. In the first column, a subsistence household is defined on the basis of imputed income and food expenditure in all periods. In the second column, a subsistence household is defined as the one being in the top 25 percentile of the ratio of annual imputed income to annual food expenditure. In the third column, a subsistence household is defined on the basis of imputed income and food expenditure in 2015. The table shows the coefficient of the interaction of subsistence household dummy and post October 2016 dummy variable in the time series regression. Rest of the specification is the same as that in table 10.

Table 12: Total expenditure by subsistence

	(1) Total expenditure
Subsistence*Post	97.94
	(231.7)
Observations	92
Raw observations	195942

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is the estimated non-durable expenditure time series after controlling for household wealth controls and household fixed effects, separately for subsistence and non-subsistence households. A subsistence household is defined as the one where the head of the household is a farmer and the ratio of annual imputed income to annual food expenditure is greater than 0. The table shows the coefficient of the interaction of subsistence household dummy and post October 2016 dummy variable in the time series regression. Other controls in the time series regression include subsistence household dummy, post October 2016 dummy, calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 to estimate the coefficient from a window around demonetization and interactions of the subsistence household dummy with the time trend and time dummy variables

Table 13: Results for those who lost employment

	(1) Borrowing from money lender	(2) Income	(3) Expenditure
Lost employment November	0.035***	-3405.7**	-604.7
	(0.007)	(1309.3)	(396.7)
Lost employment April	0.001	-4914.1***	-562.2
	(0.007)	(1465.8)	(397.3)
Observations	43	43	43
Raw obs. (November)	12304	12462	12462
Raw obs. (April)	13345	13123	13123

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The results in first row are for those households where at least one member of the household was employed in the months of August 2016, September 2016 and October 2016 but was not employed in the months of December 2016, January 2017 and February 2017. The results in the second row are for those households where at least one member of the household was employed in the months of January 2016, February 2016 and March 2016 but was not employed in the months of May 2016, June 2016 and July 2016. The dependent variables are the estimated borrowing from money lender, income and non-durable expenditure time series after controlling for household wealth controls and household fixed effects. The table shows the coefficient of the corresponding Post variable in the two rows in the time series regression. Other controls in the time series regressions include calendar month dummies to account for seasonality, linear time trend, a dummy for months six months before and a dummy for months six months after April 2017 to estimate the coefficient from a window around the employment shock.

A Data appendix

A.1 Using only the recent month of data

In the paper, I use only the recent month of income and expenditure data for all households. Here, I show evidence that households are reporting about the previous months based on their recent economic circumstances and hence, there is bias in the reported data of the months further away from the interview. To show the evidence, I focus on the sample where at least one household member lost employment after demonetization. I show these results by taking an arbitrary cutoff of July 2016 and focus on households where at least one member lost employment after July 2016. The results are similar if I take other cutoff as well. I keep the sample where at least one household member who reported being employed in the months of April-June 2016, reported being unemployed in the months August-October 2016.

Figure A.1 shows the reported income for each month for these households by the month of interview. If we look at the households who have been surveyed in August 2016 (the blue dots), these households have also been interviewed in April 2016 and in April, all the working members reported being employed but the survey does not ask about April's income until August. And in August, when one of the working members has lost employment, they report lower incomes for previous four months, including for April, when actually the employment loss had not happened. Furthermore, we see the same patterns for households being interviewed in September and October as well, that is, they report lower incomes for previous four months, including the month in which they were interviewed last and in which they reported that all the working members were actually employed.

If the reporting of each of the previous months is correct, this figure would imply that these household members lost their job right after they were interviewed and that too, for different months of survey as well, which seems unlikely. This result suggests that households are reporting their incomes of the previous months based on their current circumstances which is likely to lead to bias if we use all the data of the previous months. Therefore, I only use the recent month of data for my analysis.

Figure A.1: Reported income by month group
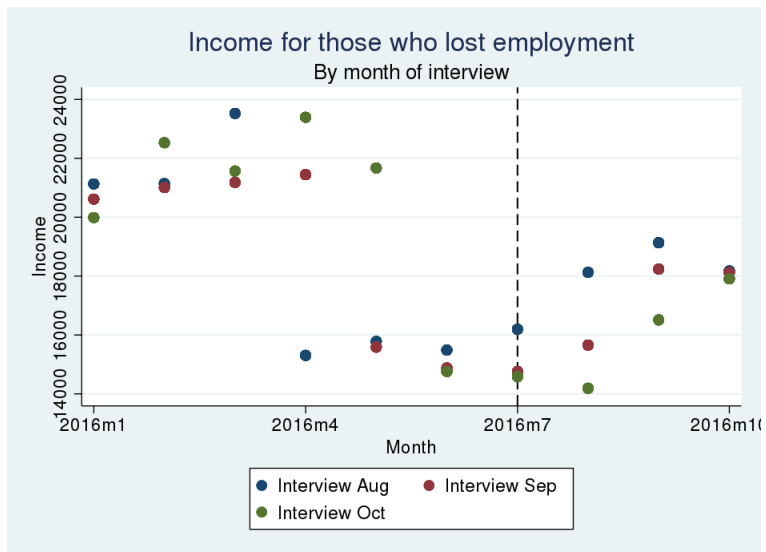
A.2   Durable consumption verification from IIP

Here, I show the quarterly growth rates from Index of Industrial Production data for consumer durables from Ministry of Statistics and Program Implementation (MOSPI) which shows that while the growth rates were positive and increasing before demonetization, there has been a decline and the growth rates have been negative throughout 2017.

Figure A.2: Index of Industrial Production- Consumer Durables
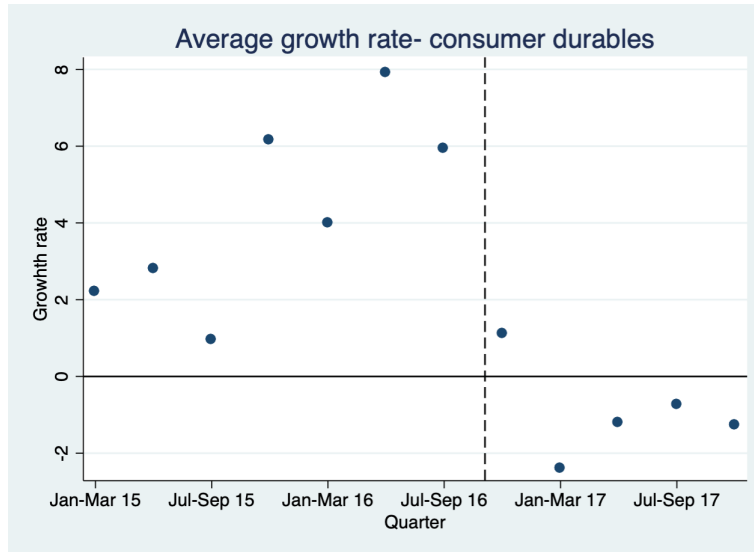
A.3   Non-durable consumption growth rates from PFCE

Here, I show the annual growth rates for some components of the Private Final Consumption Expenditure Data from MOSPI to show that non-durable consumption and in particular, consumption of many services has increased in 2017-18 which also shows up as an increase in the CMIE Consumer Pyramids Data.

Figure A.3: PFCE annual growth rates (MOSPI data)

(a) Various Services
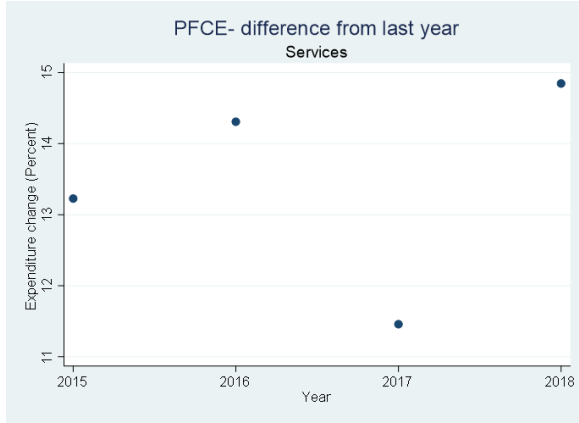
(b) Transport
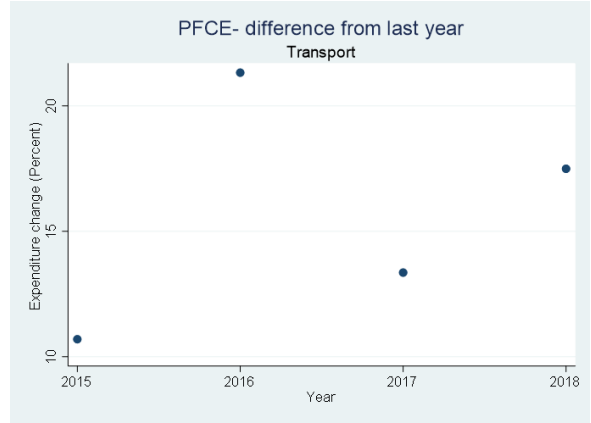
(c) Household maintenance
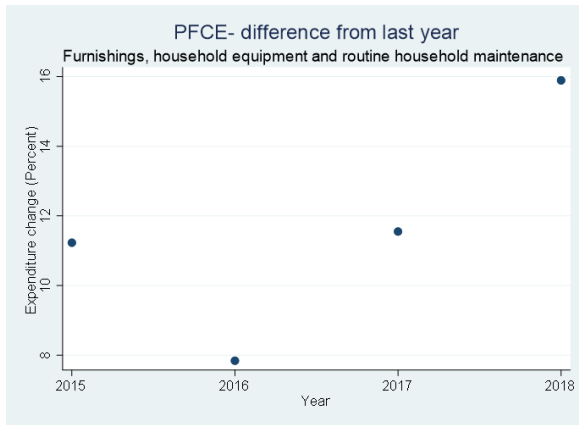
(d) Electricity and other fuels
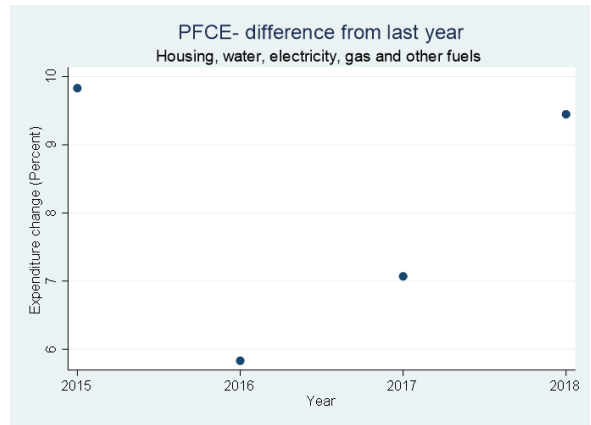
(e) Recreation
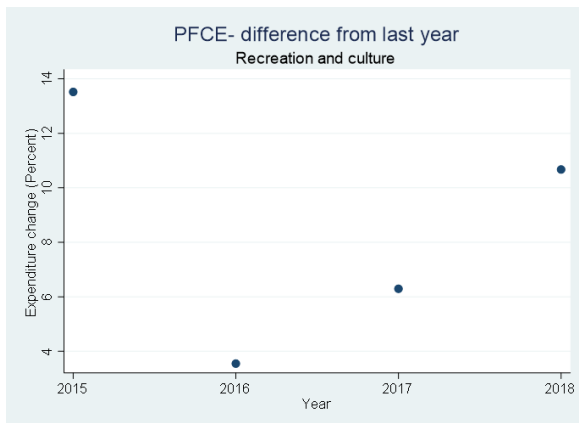
(f) Miscellaneous
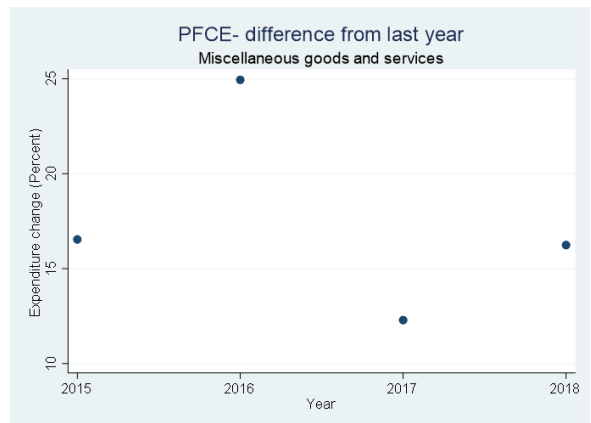
A.4   Increase in income

The Consumer Pyramids Data shows a significant increase in household income (nearly 30%) in 2017-18 and most of it is coming from the last three months of data, that is, September, October and November 2017. Here, I provide some likely explanation for that increase. First, this was a good agricultural year and therefore, we see a significant increase in the income of farmers in figure A.4 in the October of 2017.

Figure A.4: Income for farmers
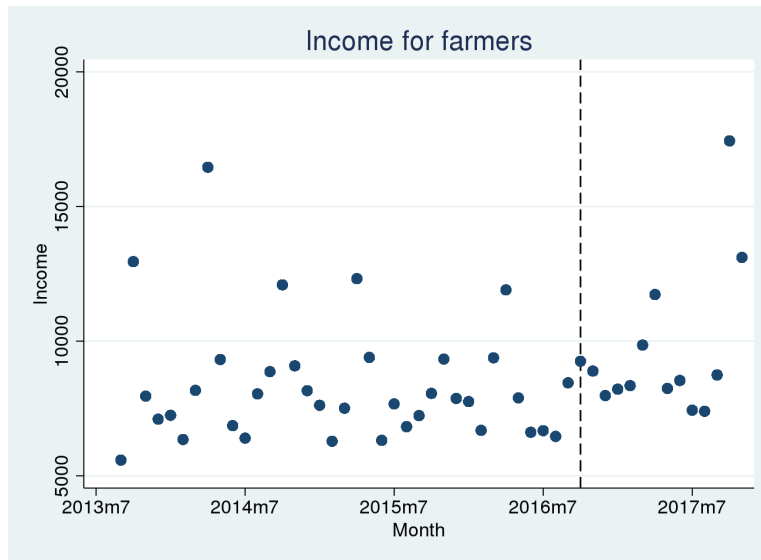
Second, Seventh Pay Commission, which significantly increased the salaries of government employees, was also being implemented in the second half of 2017 (Press Information Bureau, Government of India, July 7, 2017). While I do not observe in the occupation data whether someone is a government employee, I observe whether or not someone is a white collar employee. We can see in the figure A.5 that there has been a 25-30% increase in the income of white collar professionals.

While these two factors help in explaining some part of increase in income, it is unlikely that these factors can totally account for the increase we see in the data, particularly since the national GDP numbers do not show such a drastic increase. Thus, one other explanation here can be that if households were underreporting their incomes earlier, they are now reporting their incomes closer to the truth. While the CMIE has confirmed that there has not been any change in the way they collect this information, one way households may now be reporting higher numbers is if they are also filing more tax returns and declaring their true income to the tax authorities. Goods and Services Tax

Figure A.5: Income for white collar professionals
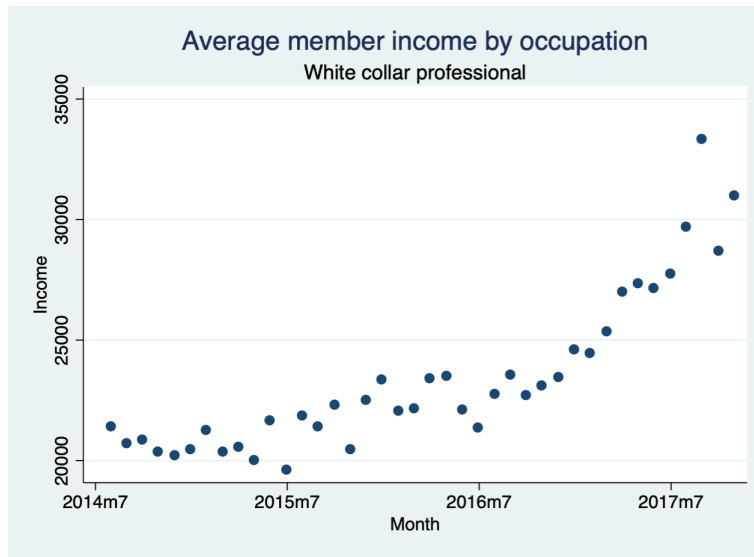
(GST) which was passed in July 2017, made many more firms and companies register themselves. We can see in figures A.6a and A.6b that there has been a significant increase in the number of companies and firms filing tax returns for 2017-18.

Figure A.6: Number of tax returns filed

(a) Companies

(b) Firms
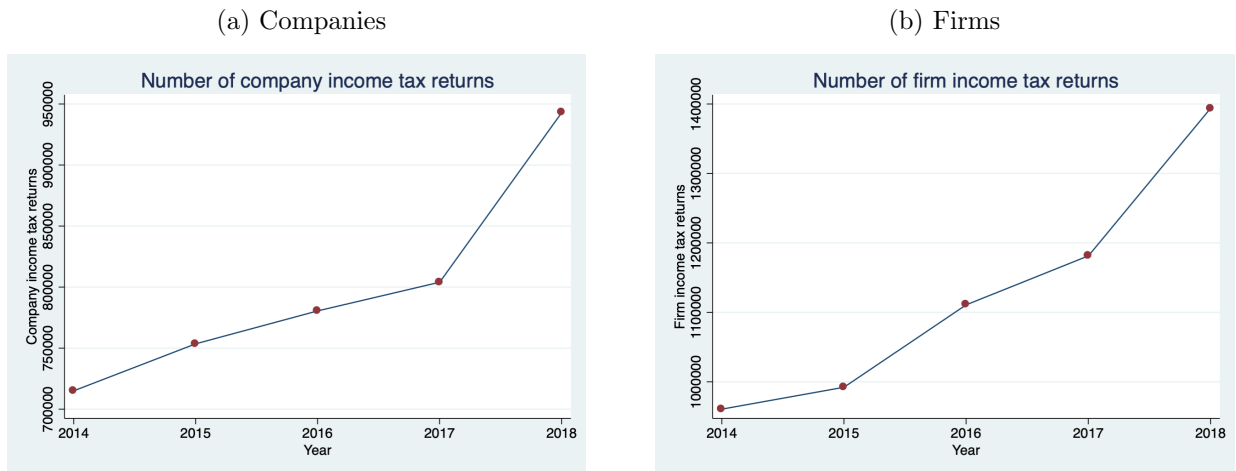
It is possible that since people are declaring incomes truthfully to the tax authorities by filing more tax returns, they also start reporting incomes truthfully in the surveys. However, this underreporting earlier is unlikely to bias the estimates since the reporting seems to change in the second half of 2017 which is not a part of the estimation window. Also, as I show in the Income subsection of Results, the estimate does not change much even when I control for this increasing pattern in the income data through a lowess time trend.

B Heterogeneity by bank branches

In this section of the appendix, I present the heterogeneity in the main outcome variables by the availability of bank branches per capita. As already mentioned in the main text of the paper, since the availability of bank branches is endogenous and possibly correlated with other indicators of development, the comparison of areas with high and low number of bank branches cannot be used to analyze the net impact of demonetization. However, this comparison can still tell us how areas with high and low number of bank branches per capita were affected differently due to the shock. For this analysis, I use the Reserve Bank of India (RBI) data on the number of commercial bank branches in each district in September 2016 (before demonetization). I combine this data with the population data from Census 2011 to construct the number of commercial bank branches per capita in each district. I test the heterogeneity by districts being *below or above the median number of bank branches per capita*.[34]

It is possible that the areas that had higher number of bank branches per capita were less affected due to the shock as in these areas, people potentially had more options to get the required cash. However, it is also possible that these areas also had higher demand for cash due to higher economic activity in these areas as compared to areas with lower number of bank branches per capita. Therefore, the direction of the effect is not obvious.

Here, I focus on the two key variables in my analysis: household non-durable consumption expenditure and borrowing from money lenders. Figure A.7 shows the non-durable consumption expenditure by districts being below or above the median number of bank branches per capita. As we can clearly see, the average expenditure is much higher in districts with above median number of bank branches per capita as compared to the expenditure in districts with below median number of bank branches per capita. This difference also shows that areas with higher number of bank branches are economically better off and therefore, are likely to be different in other economic characteristics too as compared to areas with lower number of bank branches per capita. The figure also shows that there does not seem to be a clear difference in the effect of demonetization for areas below and above median number of bank branches.

Column 1 of Table A.1 shows the regression result for the above comparison. As we can see in

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[34]The results do not change if I do the comparison by below and above *mean* number of bank branches per capita instead of median.

Figure A.7: Non-durable consumption expenditure by bank branches per capita
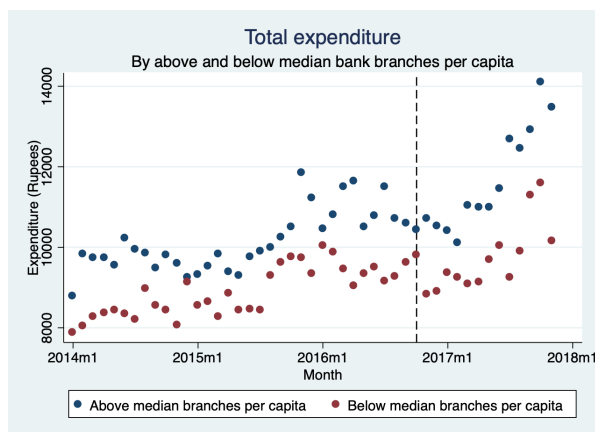
the table, we cannot reject that the coefficient on the interaction of above median bank branches and post demonetization is 0. So, there is no evidence of a statistically significant difference in effect on consumption for areas below and above median number of bank branches per capita. This result indicates that possible advantages and disadvantages of areas with higher number of bank branches potentially canceled each other out.

Figure A.8: Borrowing from money lender by bank branches per capita
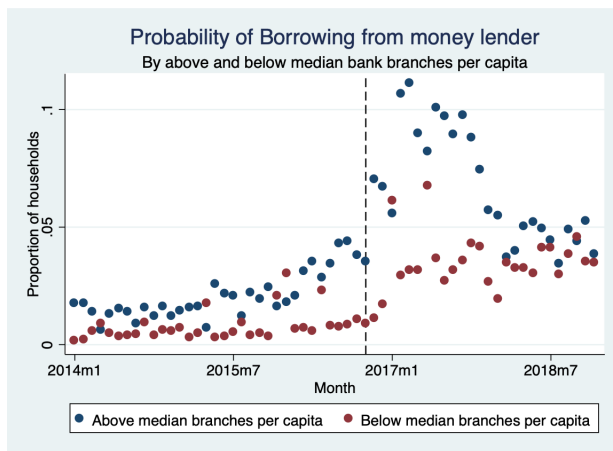
Figure A.8 shows the proportion of households having an outstanding loan from the money lender as of the date of the survey. As we can see, the districts with above median level of bank branches per capita have higher level of borrowing from money lender before demonetization. This difference could be due to money lenders being able to borrow from banks and then lending it to households. We also see that these areas also see a higher increase in probability of debt from money lenders after demonetization. Column 2 of Table A.1 shows the statistical test for this result. The interaction

coefficient shows that the borrowing from money lenders increased by around 2 percentage points more for districts having above median number of bank branches per capita as compared to below median districts. It should be noted that the result is not that precise and the coefficient is statistically significant only at 10% significance level. This result indicates that the informal credit increased more in areas with higher number of bank branches. This is likely as the areas with more bank branches would have received more cash giving more people a chance to be able to get the new currency and to be able to lend it further.

Table A.1: Heterogeneity by above and median bank branches per capita

	(1) Expenditure	(2) Borrowing from money lender
Above median expenditure	966.7* (564.5)	-0.0131 (0.0108)
Above med exp*Post	-285.0 (242.8)	0.0204* (0.0111)
Post	-766.7*** (188.2)	0.0211*** (0.00705)
Observations	92	92

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is the estimated time series of non-durable consumption expenditure (Column 1) and probability of having an outstanding borrowing from money lender (column 2), separately for households below and above the median of the bank branches per capita before demonetization, after controlling for household wealth controls and household fixed effects. The table shows the coefficient of the interaction of above median bank branches per capita dummy and post October 2016 dummy variable in the time series regression. Other controls in the time series regression include above median bank branches per capita dummy, post October 2016 dummy, calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 to estimate the coefficient from a window around demonetization and interactions of the above median bank branches per capita dummy with the time trend and time dummy variables

C   Appendix Figures

Figure A.9: Clothing and footwear expenditure
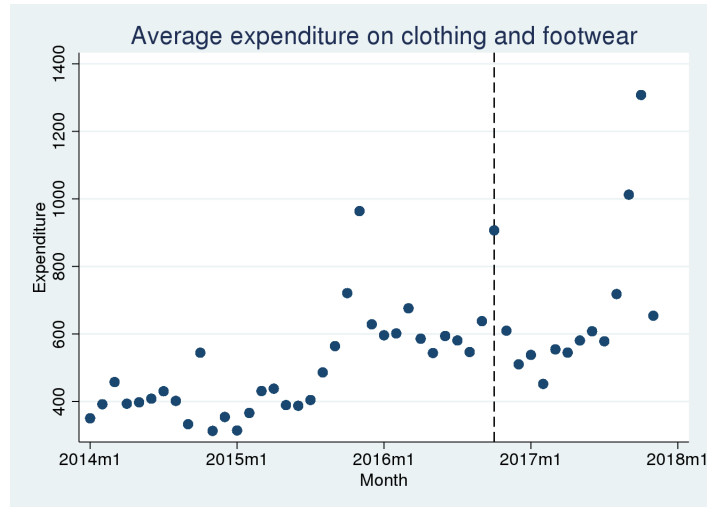
Figure A.10: Probability of buying asset in the last 4 months
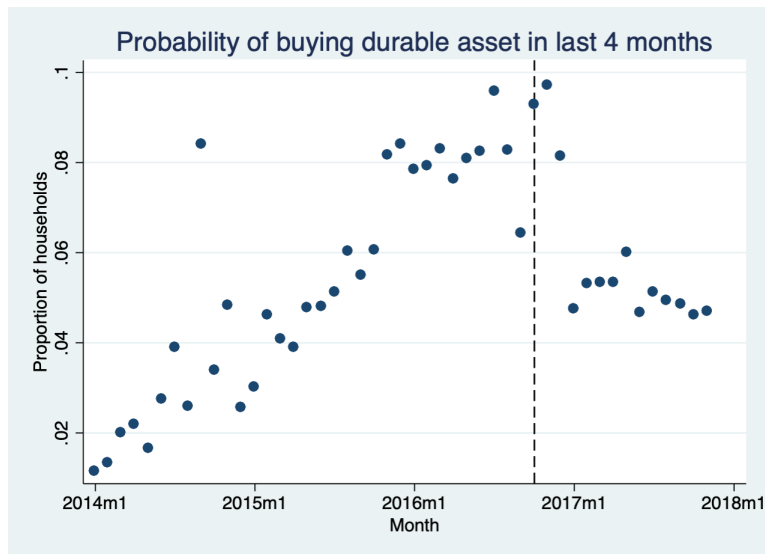
Figure A.11: Coefficients by bandwidth: probability of buying asset in the last 4 months
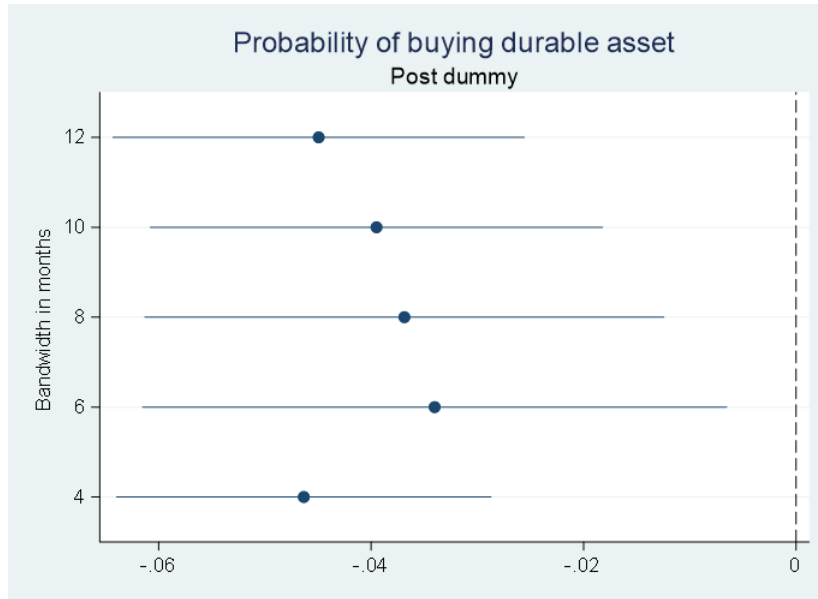
Figure A.12: Average monthly expenditure: all households
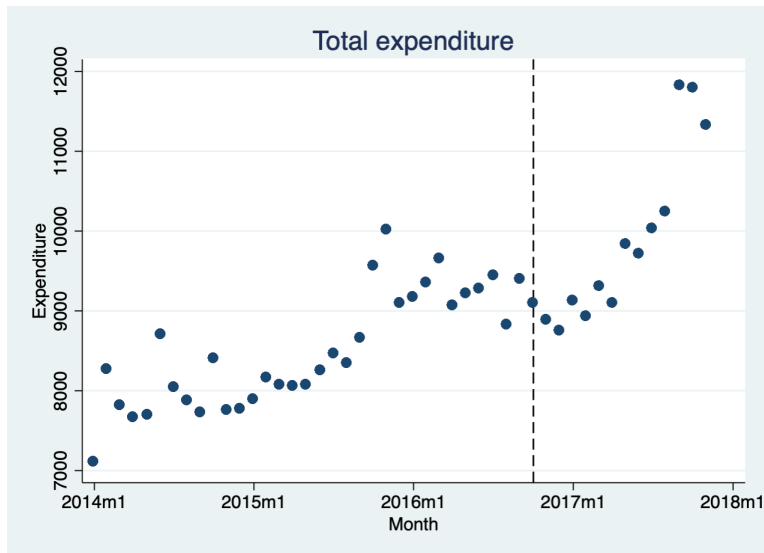
Figure A.13: Coefficients by bandwidth

(a) Expenditure
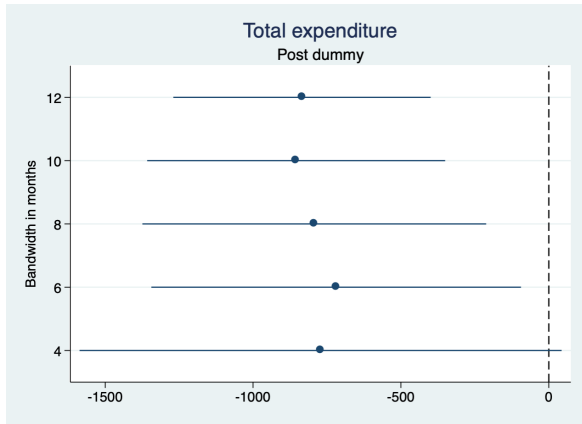
(b) CPI adjusted expenditure
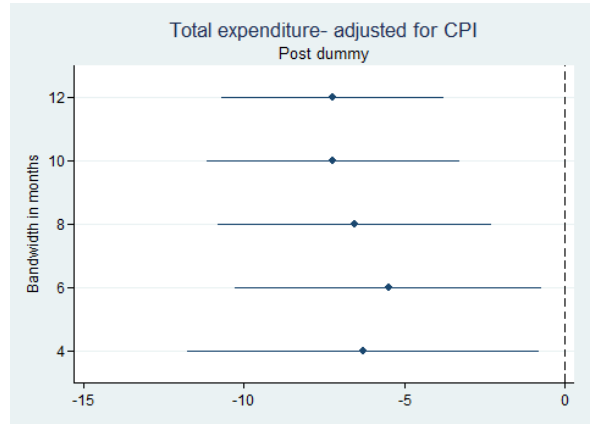
Figure A.14: Lowess plot and predicted residuals of expenditure: with controls

(a) Lowess plot
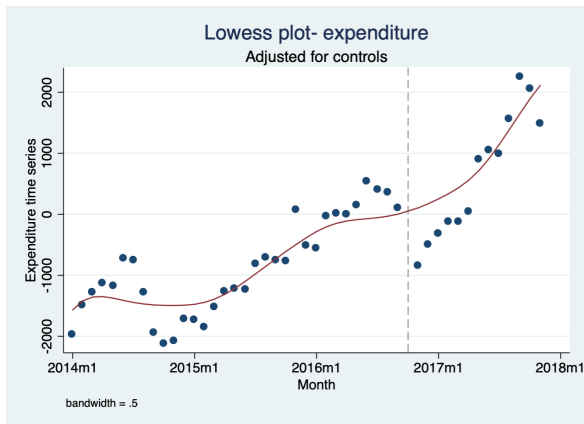
(b) Residuals
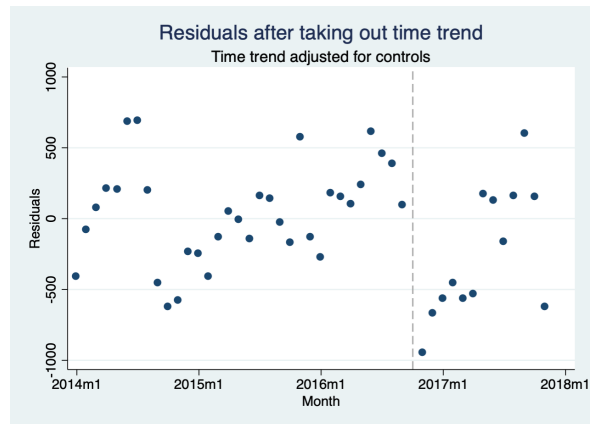
Figure A.15: Expenditure coefficient: different time trends
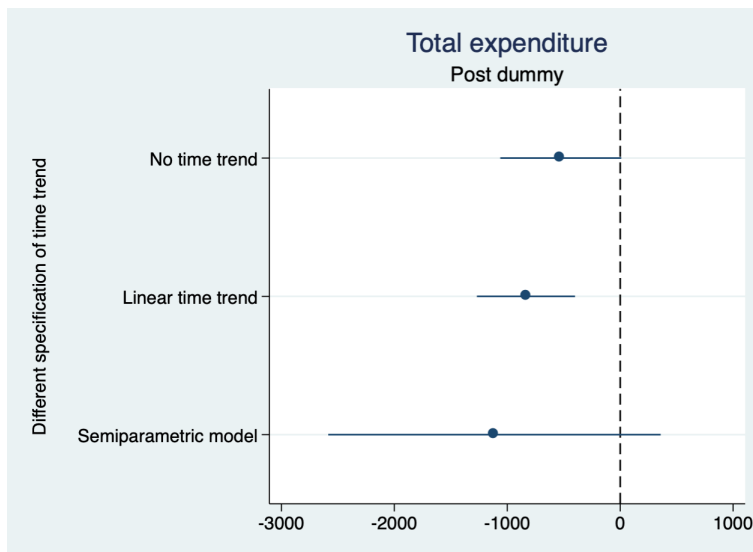
Figure A.16: Coefficients by bandwidth: Probability of borrowing from money lender
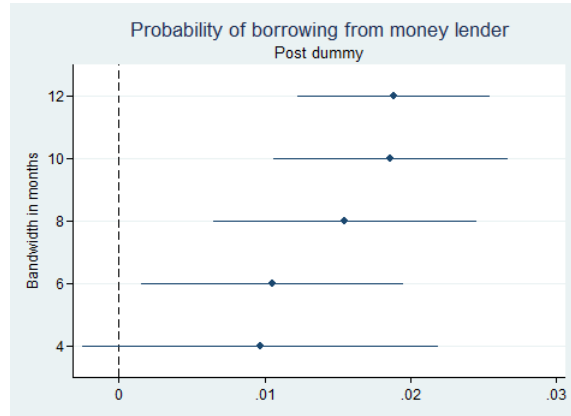
Figure A.17: Probability of borrowing from money lender

(a) By occupation

(b) By region
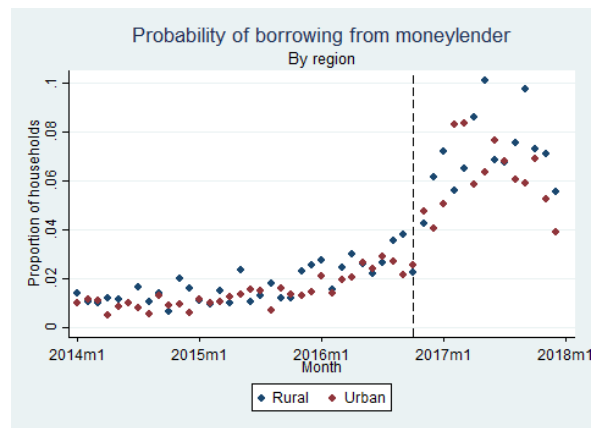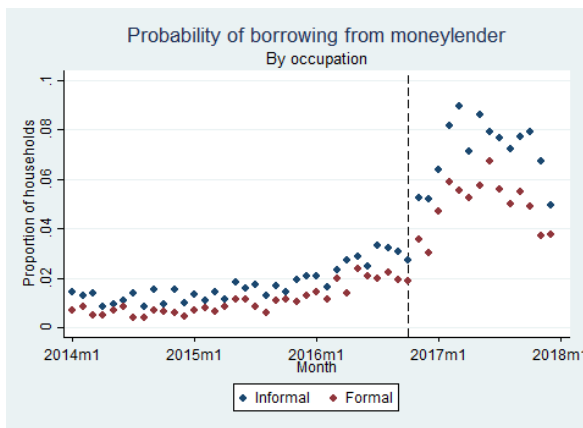
Figure A.18: Average monthly income: all households
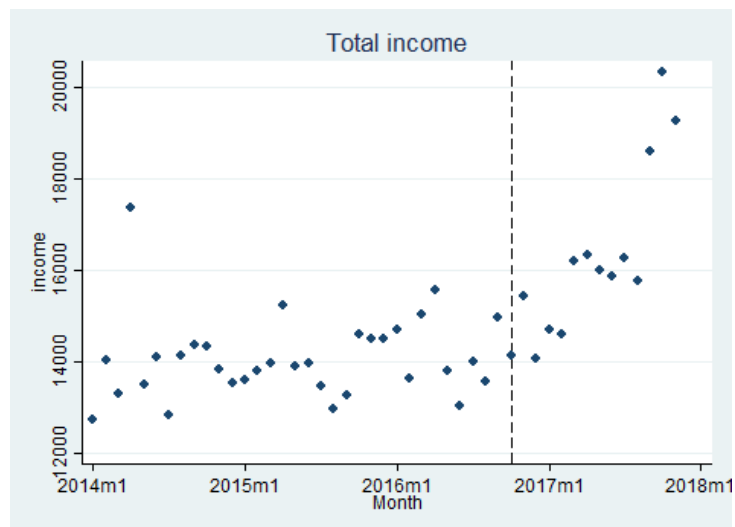
Figure A.19: Lowess plot and predicted residuals of income: bandwidth 0.5

(a) Lowess plot
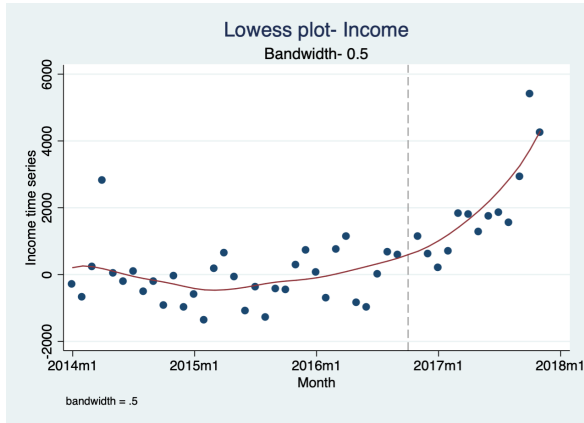
(b) Residuals
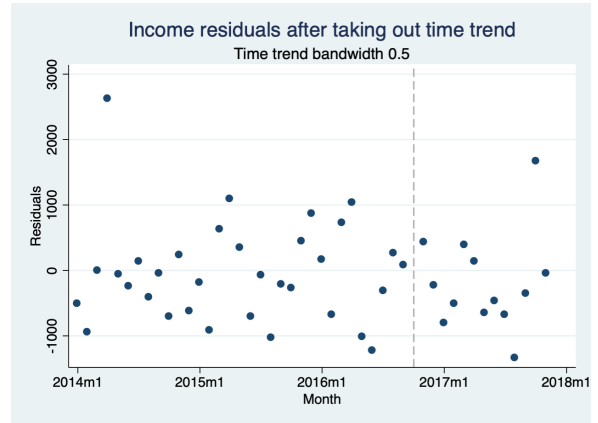
Figure A.20: Income coefficient: different time trends
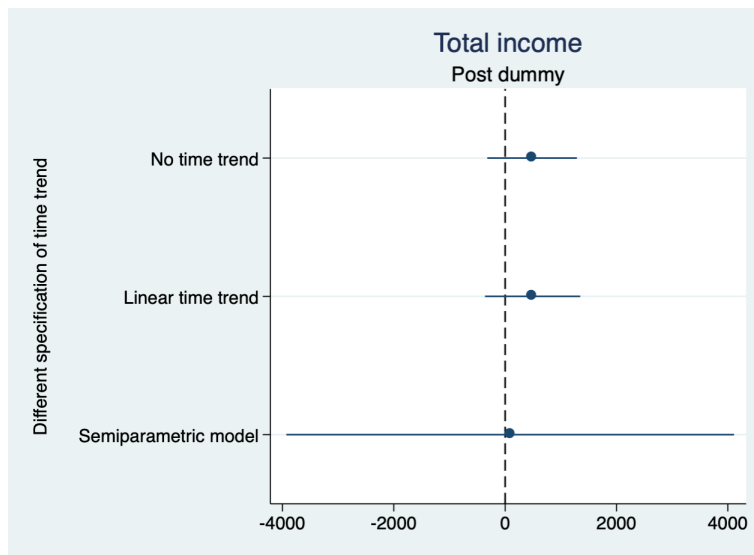
Figure A.21: Distribution of proportion of imputed income out of food: annual
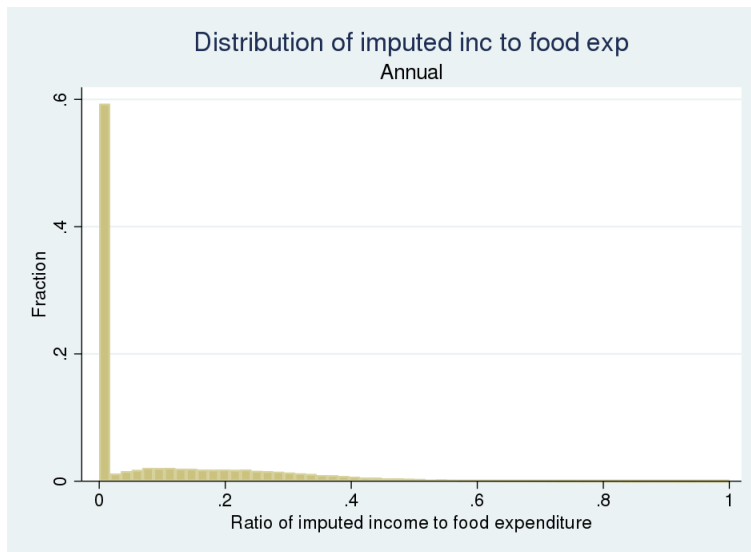
Balanced panel and individual occupations graphs

Income

Figure A.22: Average monthly income: balanced panel

(a) All households
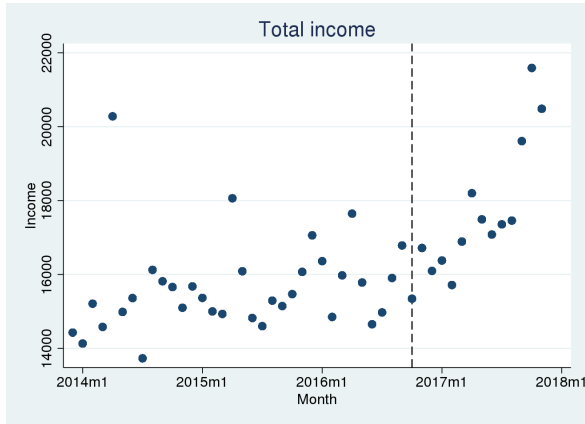
(b) Formal and Informal sector
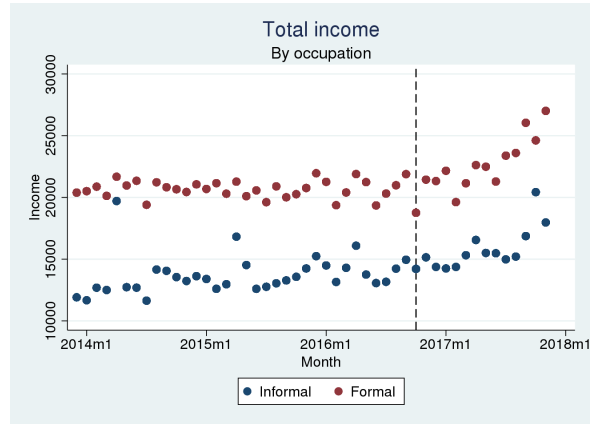
(c) By region
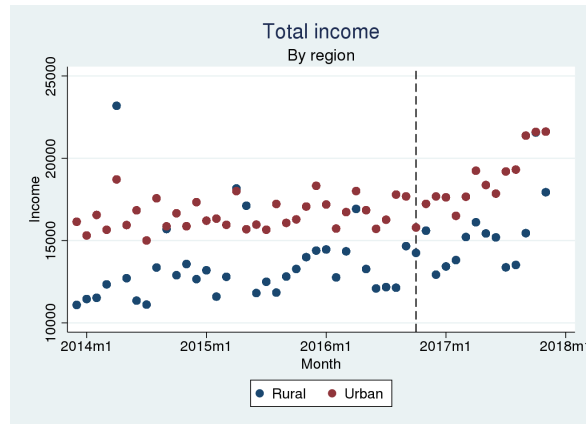
Figure A.23: Average monthly income: by occupation

(a) Agricultural Labourer
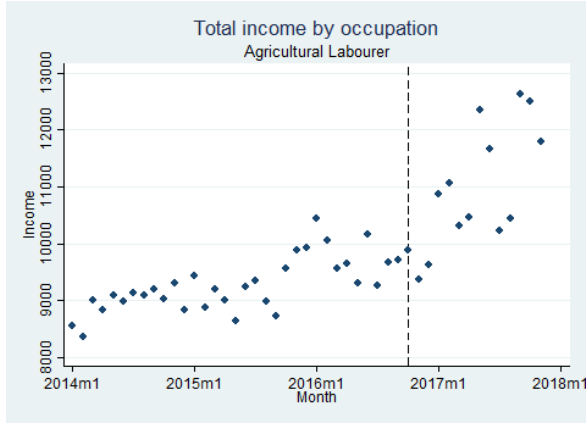
(b) Businessman
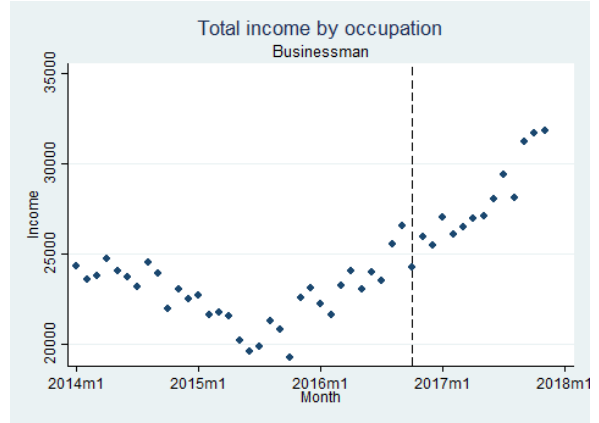
(c) Wage Labourer
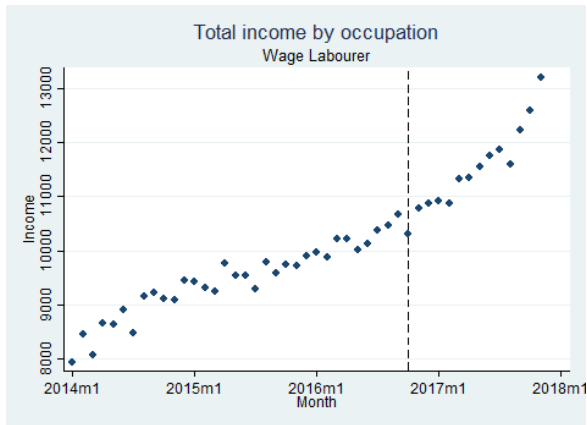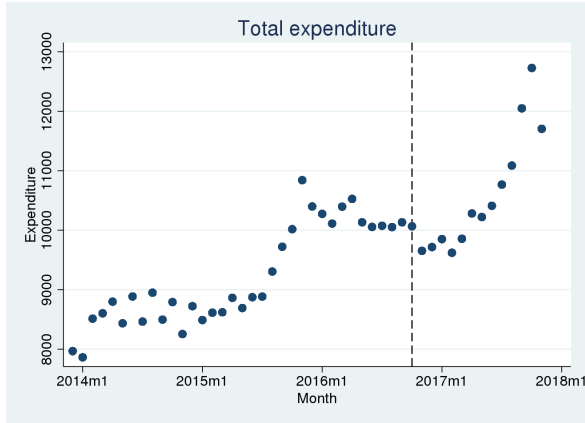

(d) Small Trader
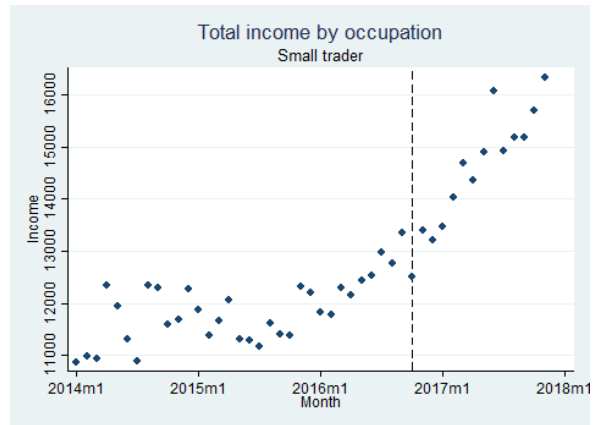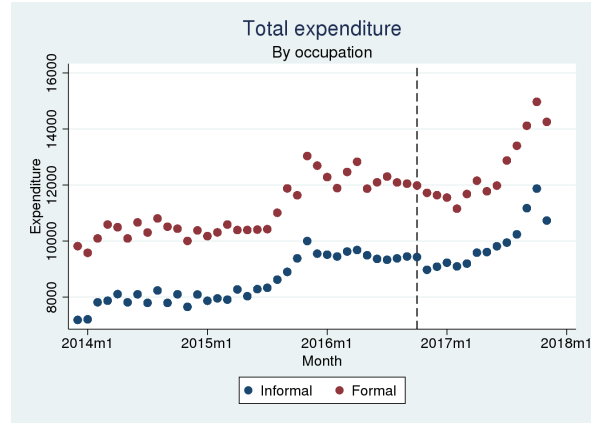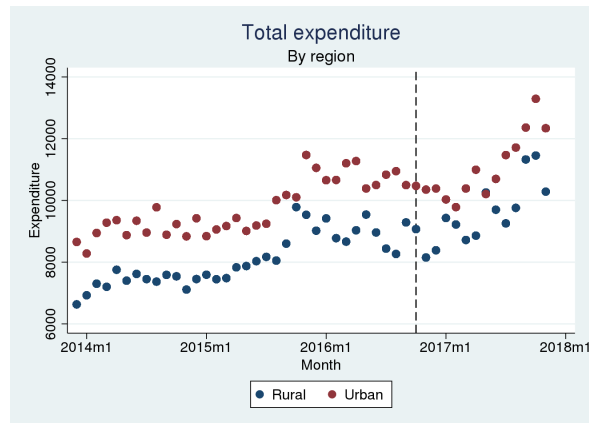

(e) Small Farmer
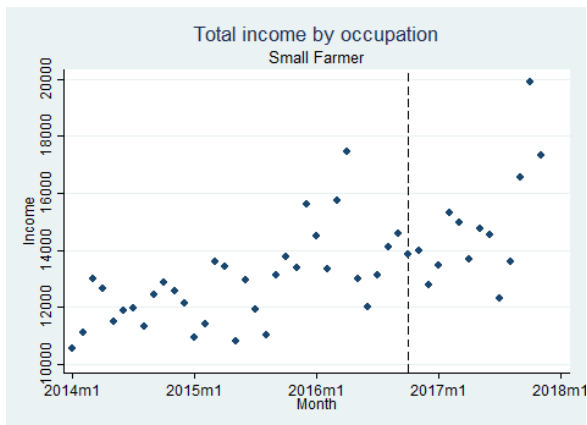
(f) White collar professional
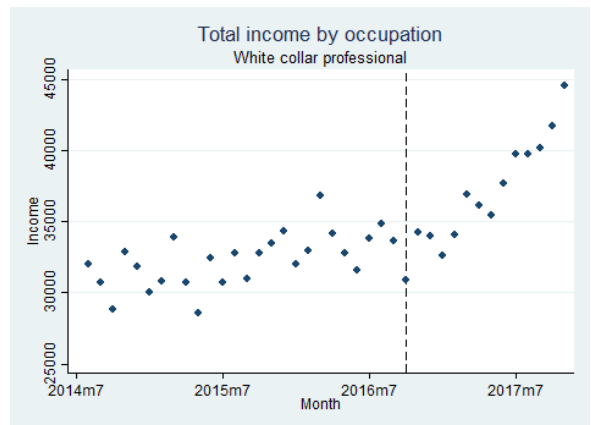
Durable purchases

Figure A.24: Probability of buying assets in last 4 months: balanced panel

(a) All households
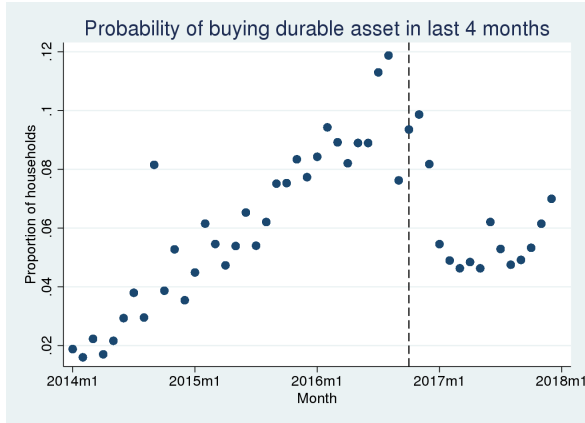
(b) Formal and Informal Households
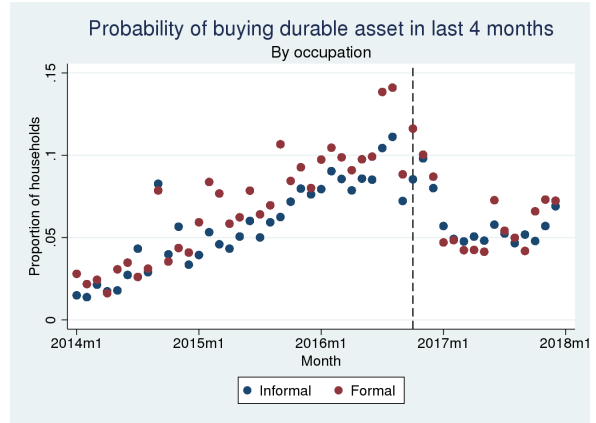
(c) By Region
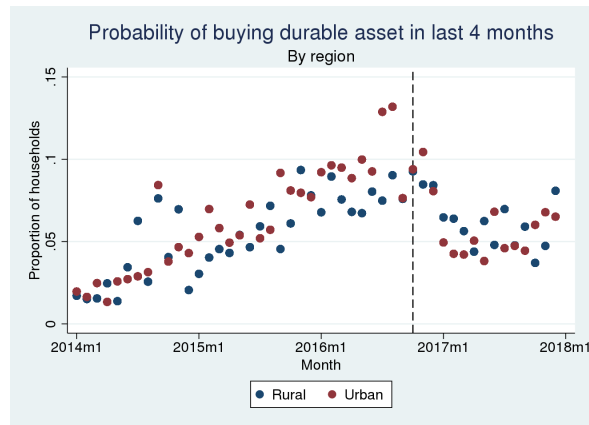
Figure A.25: Probability of buying assets in last 4 months: by occupation

(a) Agricultural Labourer
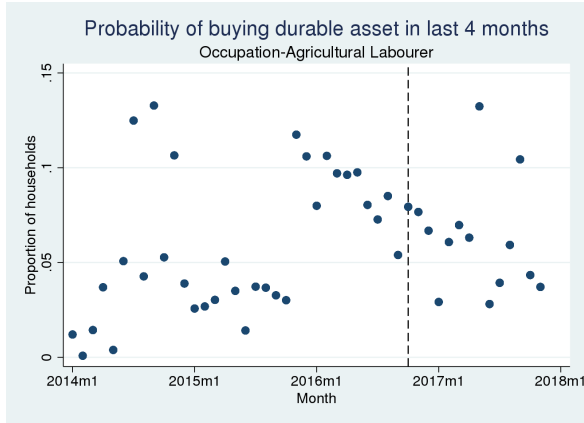
(b) Businessman
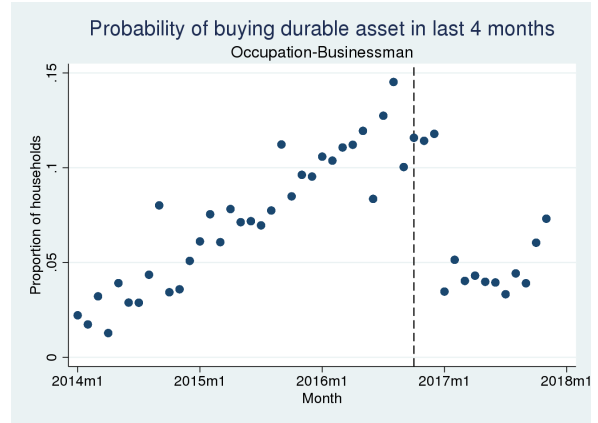
(c) Wage Labourer
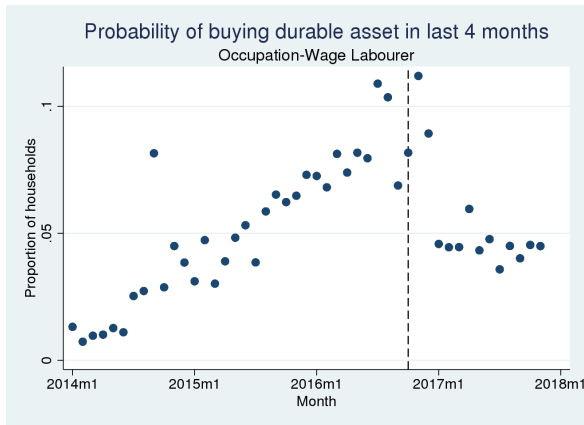
(d) Small Trader
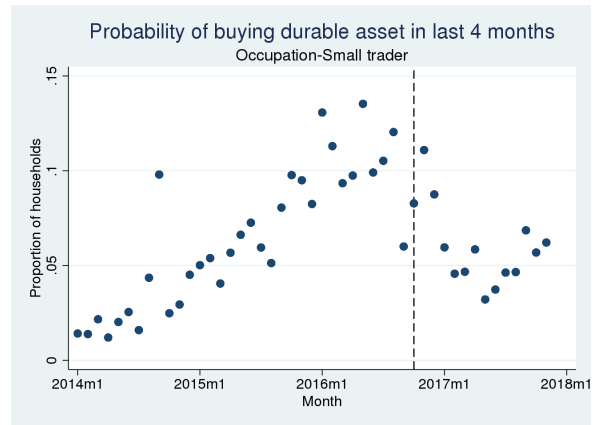
(e) Small Farmer
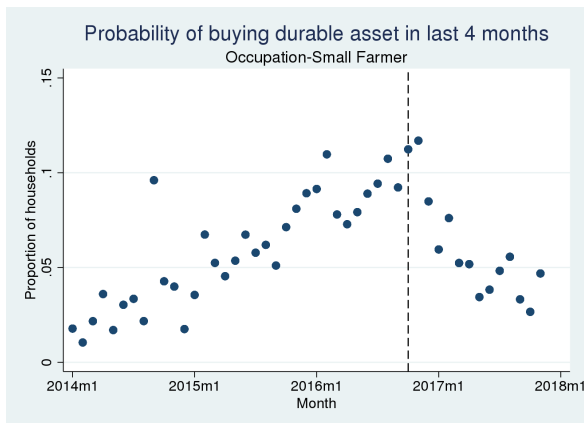
(f) White Collar Professional
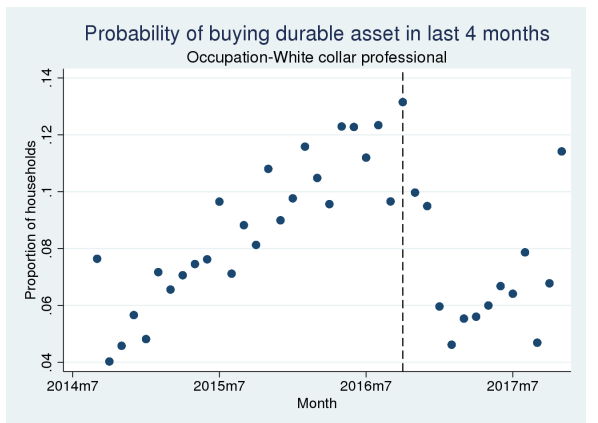
Expenditure

Figure A.26: Average monthly expenditure: balanced panel

(a) All Households
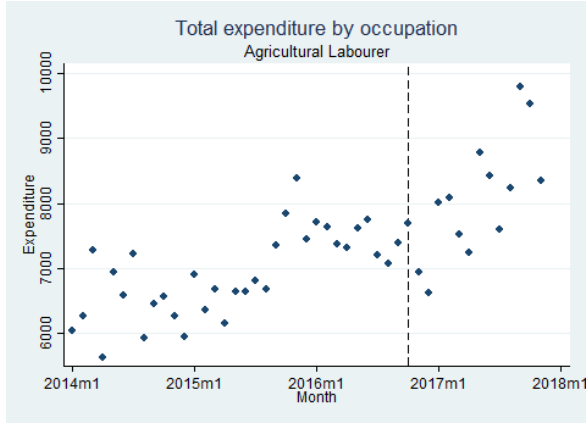
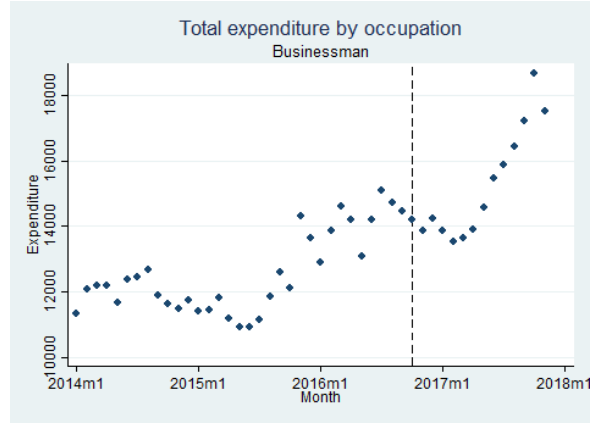(b) Formal and Informal Households

(c) By Region

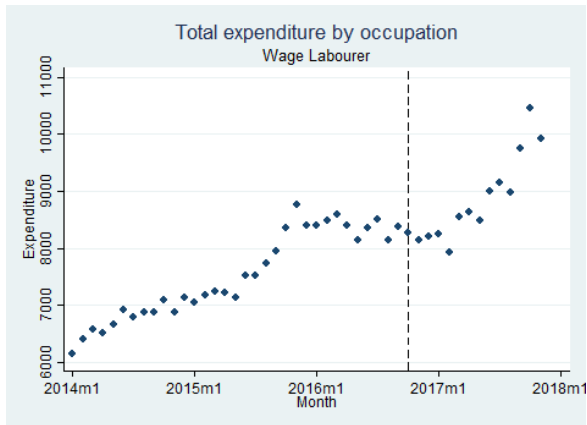Figure A.27: Average monthly expenditure: by occupation
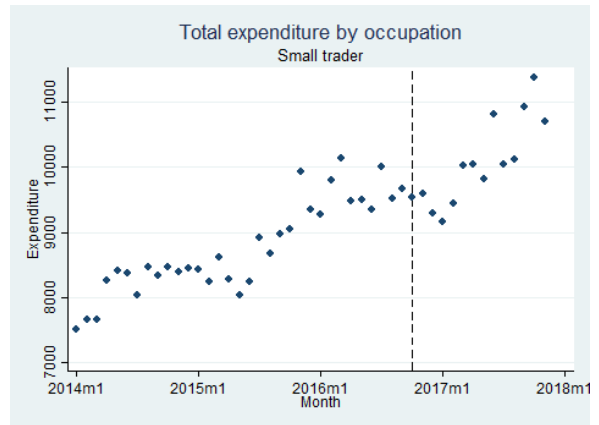
(a) Agricultural Labourer

(b) Businessman

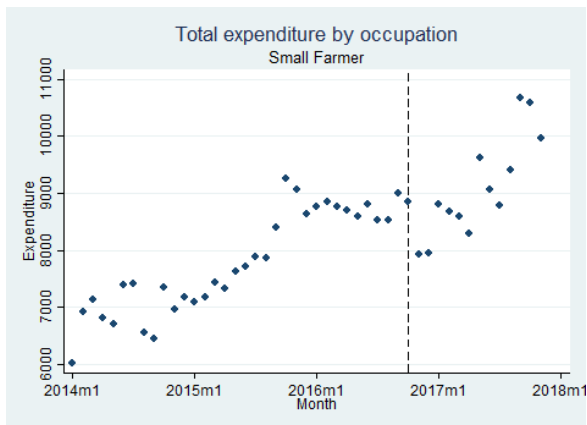
(c) Wage Labourer

(d) Small Trader

(e) Small Farmer

(f) White Collar Professional

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Borrowing from money lender

Figure A.28: Probability of borrowing from money lender: balanced panel

(a) All Households

(b) Formal and Informal Households

(c) By Region

Figure A.29: Probability of borrowing from money lender: by occupation

(a) Agricultural Labourer

(b) Businessman

(c) Wage Labourer
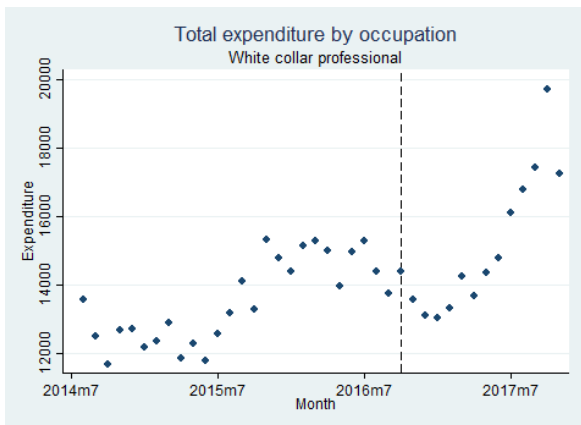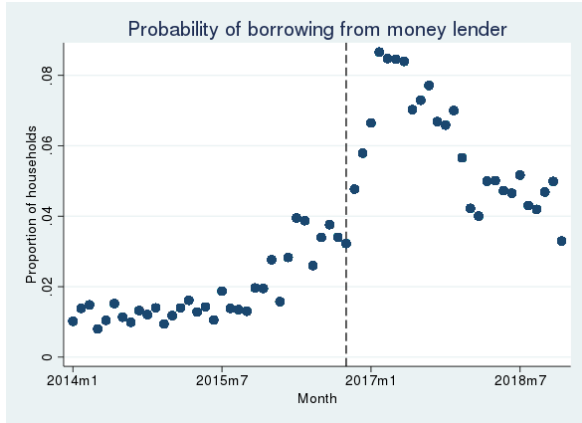
(d) Small Trader
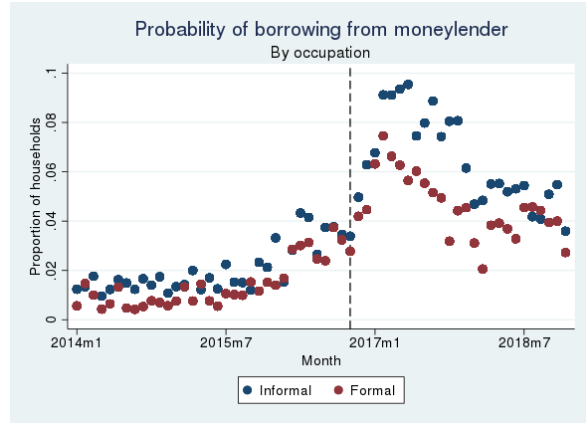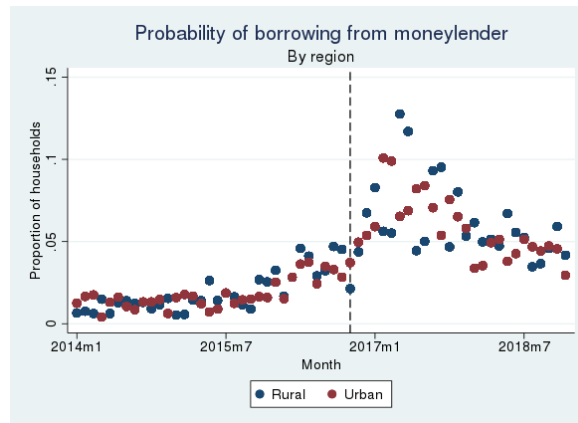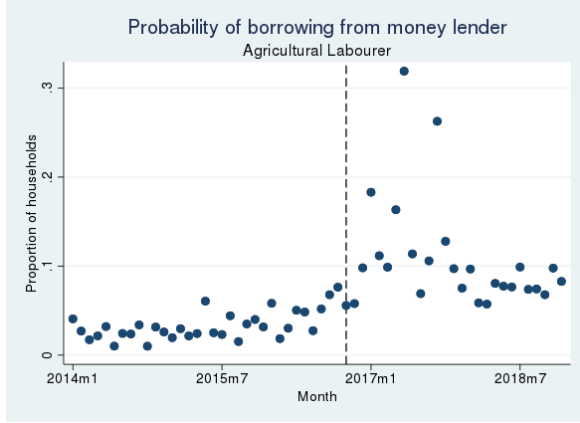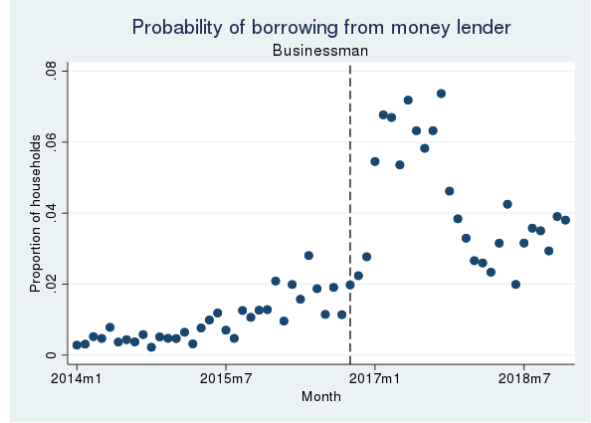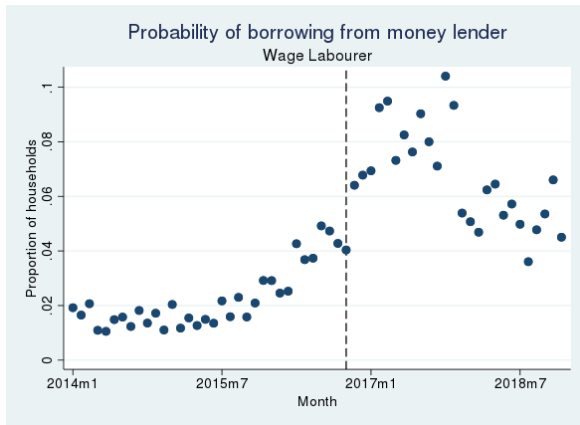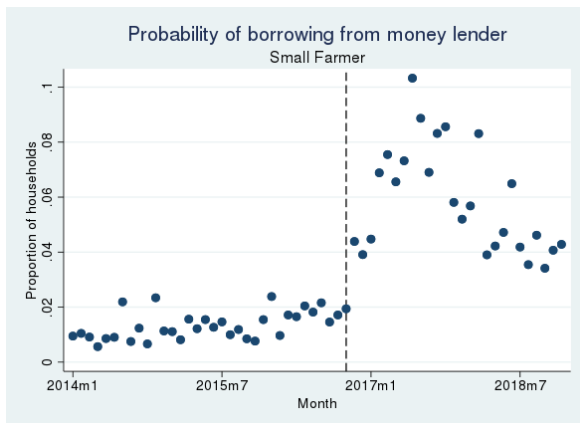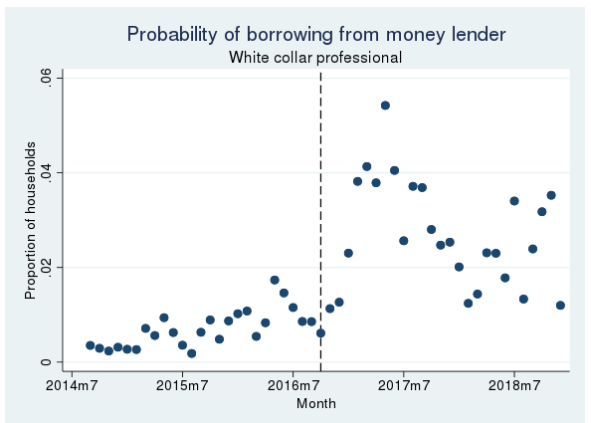

(e) Small Farmer

(f) White Collar Professional

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Subsistence households

Figure A.30: Probability of borrowing for subsistence and non-subsistence households- all periods def
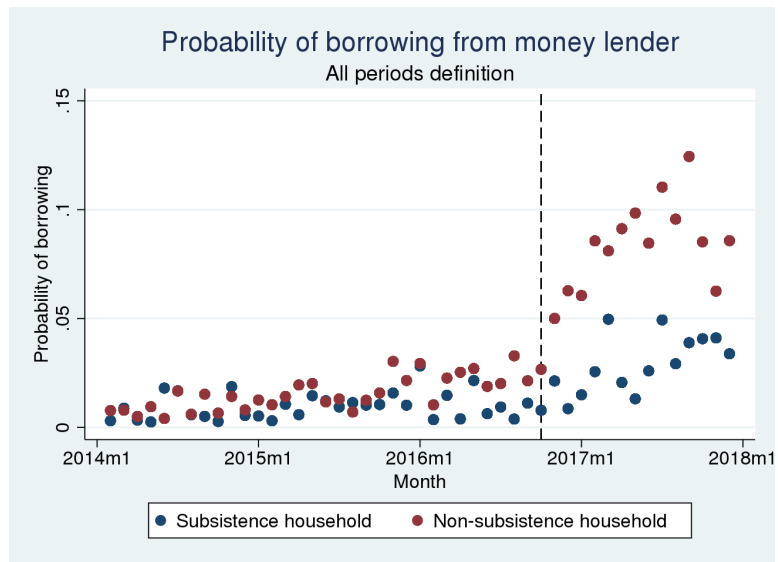
D   Appendix Tables

Table A.2: Covariates check by month of interview

	(1)	(2)	(3)	(4)
	May 2016	June 2016	July 2016	August 2016
Proportion formal	0.283	0.278	0.267	0.264
	(0.451)	(0.448)	(0.442)	(0.441)
Years of schooling	7.279	7.279	6.985	7.179
	(5.442)	(5.328)	(5.300)	(5.305)
Proportion head male	0.880	0.882	0.877	0.884
	(0.325)	(0.323)	(0.328)	(0.320)
Age in years	50.39	49.83	49.52	49.76
	(12.54)	(12.39)	(12.41)	(12.45)
Health Insurance	0.106	0.101	0.104	0.0947
	(0.308)	(0.301)	(0.305)	(0.293)
Bank branches	397.8	348.6	379.1	358.7
	(350.9)	(279.9)	(305.3)	(315.3)
Branches per capita	1.268	1.145	1.231	1.317
	(0.768)	(0.576)	(0.703)	(0.829)
Total income	17239.9	15427.4	15147.4	16038.4
	(19589.6)	(15380.2)	(13929.5)	(15581.6)
Total expenditure	10703.1	9911.3	10533.7	10470.0
	(8280.1)	(6438.0)	(11775.3)	(7778.5)
Food expenditure	4886.5	4679.1	4758.1	4768.8
	(1880.0)	(1954.5)	(1888.2)	(1980.7)
Observations	30217	33669	32570	31752

The table provides averages of the above variables for households interviewed in May, June, July and August of 2016 respectively.

Table A.3: Basic sample properties

	(1) Average
Proportion rural	0.308
	(0.461)
Number of waves observed for	9.922
	(2.454)
Years of schooling of household head	7.454
	(5.265)
Has credit card	0.035
	(0.17)
Observations	1630461

The table provides some key characteristics of the data. Entire sample is used for this table. The characteristics of the household head, including years of schooling and the probability of having a credit card are based on period before November 2016.

Table A.4: Total expenditure- controlling for oil price

	(1) Total expenditure
Post demonetization	-1448.9***
	(288.4)
Oil price	-76.24***
	(20.10)
Oil price square	0.707***
	(0.120)
Observations	46

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is the estimated non-durable expenditure time series after controlling for household wealth controls and household fixed effects. The table shows the coefficient of the post October 2016 dummy variable in the time series regression, oil price in US and the square of the oil price. Other controls in the time series regression include calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 to estimate the coefficient from a window around demonetization.

Table A.5: Categories of consumption

	(1) Food	(2) Clothing-footwear	(3) Education	(4) Health	(5) Bills-rent	(6) Power-fuel
Post demonetization	-362.7***	-161.1***	-146.9***	-27.34***	-11.24	44.84
	(35.76)	(55.52)	(32.52)	(7.832)	(7.103)	(51.14)
Observations	46	46	46	46	46	46
Mean (Rupees)	4670	490	384	200	120	1539

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable in each column is the estimated non-durable expenditure time series after controlling for household wealth controls and household fixed effects, for each category of the expenditure. The table shows the coefficient of the post October 2016 dummy variable in the time series regression. Other controls in the time series regression include calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 to estimate the coefficient from a window around demonetization.

Table A.6: Household expenditure: Non-collapsed regression

	Non-durable consumption expenditure
Post demonetization	-843.787***
	(174.980)
Period before 6 months	-50.747
	(188.455)
Period after 6 months	1104.203***
	(213.765)
Linear time trend	58.743***
	(10.003)
Observations	1547996

* $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

The dependent variable is non-durable consumption expenditure. Post demonetization refers to a dummy for post October-2016. Period before 6 months refers to a dummy for months before April 2016 and Period after 6 months refers to a dummy for months after April 2017. Other controls include calendar month dummies, household wealth controls and household fixed effects. Standard errors clustered at month level.

Table A.7: Household expenditure: Non-collapsed regression

	Non-durable consumption expenditure
Post demonetization	-218.278
	(157.882)
Period before 6 months	294.632*
	(159.339)
Period after 6 months	709.503***
	(166.281)
Above median exp*Post	-1241.086***
	(142.618)
Above median exp*Period before	-678.560***
	(139.210)
Above median exp*Period after	805.160***
	(172.567)
Observations	1527949

* $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

Above median expenditure variable omitted due to collinearity

The dependent variable is non-durable consumption expenditure. Post demonetization refers to a dummy for post October-2016. Period before 6 months refers to a dummy for months before April 2016 and Period after 6 months refers

to a dummy for months after April 2017. Other controls include calendar month dummies, household wealth controls and household fixed effects. Standard errors clustered at month level. Above median expenditure refers to a dummy which takes value 1 for the households with above median average household non-durable expenditure before November 2016.

Table A.8: Borrowing from money lender

	Probability of borrowing from money lender
Post demonetization	0.035***
	(0.004)
Period before 6 months	-0.005*
	(0.002)
Period after 6 months	0.002
	(0.004)
Linear time trend	0.000***
	(0.000)
Observations	1596753

* $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$

The dependent variable is the dummy for having outstanding borrowing from money lender. Post demonetization refers to a dummy for post October-2016. Period before 6 months refers to a dummy for months before April 2016 and Period after 6 months refers to a dummy for months after April 2017. Other controls include calendar month dummies, household wealth controls and household fixed effects. Standard errors clustered at month level.

Table A.9: Borrowing from money lender

	Probability of borrowing from money lender
Post demonetization	0.053***
	(0.006)
Period before 6 months	-0.009***
	(0.003)
Period after 6 months	-0.001
	(0.007)
Above median exp*Post	-0.028***
	(0.005)
Above median exp*Period before	0.008***
	(0.002)
Above median exp*Period after	0.003
	(0.006)
Observations.	1528375

* $p < 0.10$, ** $p < 0.05$, ***$p < 0.01$
Above median expenditure variable omitted due to collinearity

The dependent variable is the dummy for having an outstanding borrowing from money lender. Post demonetization refers to a dummy for post October-2016. Period before 6 months refers to a dummy for months before April 2016

and Period after 6 months refers to a dummy for months after April 2017. Other controls include calendar month dummies, household wealth controls and household fixed effects. Standard errors clustered at month level. Above median expenditure refers to a dummy which takes value 1 for the households with above median average household non-durable expenditure before November 2016.

Table A.10: Borrowing from money lender by occupation

	(1) Probability of borrowing
Formal*post	-0.0144**
	(0.00587)
Observations	92

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is the estimated time series of probability of having an outstanding borrowing from money lender after controlling for household wealth controls and household fixed effects, separately for formal and informal occupations. The table shows the coefficient of the interaction of formal occupation dummy and post October 2016 dummy variable in the time series regression. Other controls in the time series regression include formal occupation dummy, post October 2016 dummy, calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 to estimate the coefficient from a window around demonetization and interactions of the formal occupation dummy with the time trend and time dummy variables

Table A.11: Total income by occupation

	(1) Income
Formal*post	725.6
	(560.7)
Observations	92

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

The dependent variable is the estimated income time series, separately for formal and informal occupations, after controlling for household wealth controls and household fixed effects. The table shows the coefficient of the interaction of formal occupation dummy and post October 2016 dummy variable in the time series regression. Other controls in the time series regression include formal occupation dummy, post October 2016 dummy, calendar month dummies to account for seasonality, linear time trend, a dummy for months before April 2016 and a dummy for months after April 2017 to estimate the coefficient from a window around demonetization and interactions of the formal occupation dummy with the time trend and time dummy variables.