Was India's Demonetization Redistributive? Insights from Satellites and Surveys.*

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Abstract

On November 8, 2016, the Indian government abruptly demonetized 86% of its currency in circulation in an attempt to reduce black money, corruption, and counterfeiting. Yet, 99% of the currency was eventually returned to banks. We show that both *poorer* regions and *poorer* households experienced relative and absolute increases in economic outcomes over the year and a half that followed. For the regional analysis, using monthly night-light data, we estimate a one standard deviation increase in deposits was associated with about 4% increase in district GDP per capita. The districts that experienced large deposit increases from demonetization are generally poorer, or worse off, in several widely used measures of socio-economic characteristics. For the household analysis, using a longitudinal survey of expenditures and incomes, we also show that poorer households had larger relative increases in expenditures and incomes in the following eighteen months.

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1 Introduction

On November 8, 2016, the Indian government announced large currency denomination notes would no longer be considered legal tender and, with few exceptions, had to be deposited into banks by the end of the calendar year. These notes (in ₹500 and ₹1000 denominations) accounted for 86% of currency in circulation. For a country like India, where almost ninety percent of transactions take place in cash, such an abrupt announcement threw the economy into chaos. The avowed goals of the policy were reducing the volume of the "black economy", increasing the tax base, and reducing funding sources for terrorist activities. There is considerable, if not outright skepticism, whether the policy achieved any of these. It is generally accepted that it reduced economic growth in the last quarter of 2016 and also to some extent in the first quarter of 2017. In this research, we investigate regional and household outcomes over approximately a year and a half following demonetization (till April 2018). We show that districts that recorded higher deposit growth during the last quarter of 2016 experienced greater *increases* in nighttime lights throughout 2017 and early 2018. We also document that the poorer districts are the ones which experienced the largest growth in deposits from demonetization, and as a result are driving the post-demonetization increase in nightlights. We complement our regional results by also examining household level data from a large panel, and show that those in the poorest quintiles saw larger growth in both expenditures and income relative to the richest.

Our research overwhelmingly suggests that over the medium term, the effects of demonetization across regions and households has been re-distributive. These findings stands in sharp contrast, though not necessarily contradictory, to much of the popular narrative and the emerging research that provides evidence in support of the opposite in months immediately following the announcement, e.g. Chodorow-Reich et al. (2020). While the results of our study might at first appear counter-intuitive and highlight unintended consequences of the policy, they are motivated by a number of observations. First, the overall aggregate effects as measured by official real GDP statistics seem to have been rather benign - about 0.5 to 1% reduction in annual growth. Chodorow-Reich et al. (2020), also using night-light data, estimate a 2.5% reduction in GDP during that quarter, with the negative shock dissipating thereafter. Indeed, Lahiri (2020) notes the discrepancy between the aggregate outcomes reflected in the GDP numbers, and some of the negative short run effects in research using disaggregated data. Second, as shown in Figures 1 and 4, and discussed at length later, the monthly night light data and surveyed household income and expenditures exhibit clear upward trajectories during most of 2017 despite being relatively stagnant between 2014 and 2016. The increase in nighttime lights is particularly striking since one of the avowed benefits of night light data is that it can substitute dubious official statistics.

Third, those who had undisclosed currency clearly figured out ways to launder their cash. These methods, which emerged quickly and were widespread, included channeling currency notes through accounts of employees, brokers who found low income households or zero balance account holders, advance salary payments to employees, settlement of debts, or even finding businesses (usually informal) who were willing to sell goods at a markup if purchased with the defunct notes. Invariably, all of these methods involved paying premiums or commissions to the intermediaries and ultimate depositors.[1] Back-of-the-envelope calculations in Section 4, suggest a 10% redistribution of funds potentially amounted 0.4% in GDP—a magnitude similar in size to the rebate checks of US's American Recovery and Reinvestment Act of 2009. Fourth, despite the economic chaos during the initial two months, the policy was viewed favorably, suggesting that the government might have successfully altered expectations regarding future policy making and growth, especially among the poor and middle class. Indeed, Narender Modi's Bhartiya Janata Party (BJP) was re-elected resoundingly in the national elections held in April 2019.[2] To summarize, our finding of redistribution can easily reconcile the facts that 99% of the money was returned indicating almost no wealth was lost in the aggregate, any negative GDP effects were mild and short lived, the BJP did not pay a political price (and, on the contrary, increased its support), and the money laundering that took place on a national scale.

Since the entire country was subject to the treatment simultaneously, our estimation strategy for the regional analysis, which constitutes the first part of our empirical investigation, exploits two sources of variation. First, we exploit the panel data nature of our district sample to separate the pre, during (the two implementation months), and post periods. Second, we exploit cross-sectional variation at the district level by using deposit growth during the demonetization quarter to capture the intensity of treatment. More specifically, we calculate the growth (i.e., the percent change) in total outstanding bank deposits between the end of the third quarter of 2016 (i.e the quarter before demonetization was implemented) and the end of the fourth quarter of 2016 (the deadline for depositing discontinued notes). Our approach, which relies on the interaction between the two sources of variation, is thus analogous to a difference in difference strategy.[3] Using monthly nighttime lights as our outcome variable, we show that districts that experienced a higher growth in deposits from

[1] See KPMG (2016) and Rajagopalan (2020) for a description of these methods.

[2] The elections were held after initial work began on the current paper. Banerjee and Kala (2019) note that despite suffering approximately 20% decline in their sales, traders surveyed in Bengaluru had an overwhelmingly positive view of the policy. Further, using data from produce markets and state election results in Uttar Pradesh, they estimate a 100% decline in sales was associated with only a 1% decrease in the vote share of the BJP.

[3] Burgess and Pande (2005) employ a similar strategy to examine the expansion of rural banking in India, while Nunn and Qian (2011) apply it to study the effects of the introduction of potato cultivation on historical urbanization and population growth in Europe.

demonetization had a) lower values of log night time lights during the two months when currency restrictions were in place, and b) recorded higher values of log nighttime lights in the post demonetization period (i.e., from January 2017 to April 2018) which more than offset the earlier reduction. We subject our estimation to a range of robustness checks including checking for parallel trends, time trends, month effects, placebo tests, monthly rainfall and cloud cover, geography based post trends, etc.

The huge shortage of replacement currency in the last two months of 2016 makes deposit growth in that quarter appealing as a *proximate* measure of a district's exposure to demonetization. First, it allows us, as it were, to "follow the money". This stems from the nature of branch banking in India. As a hypothetical example, consider a migrant worker in New Delhi. Usually the worker makes monthly deposits in the Delhi branch to remit money into an account that is located in their home district. In other words, deposit growth would show up in the home district, and not Delhi. Second, contrary to expectations, 99% of the demonetized currency notes were returned. This was despite the fact that the Indian government, in an effort to punish those with unaccounted cash, introduced additional rules regarding the amount of discontinued currency that could be deposited into a bank account.[4] Irrespective of whether currency notes were deposited within the same district, or redirected into adjoining districts or, as we shall note later, even across the country, deposit growth captures where it ended up going. To summarize, even though the vast majority of deposit growth undoubtedly reflected cash shortage, it also helps us examine the economic activity of regions where the money was finally deposited. One might be concerned about the appropriateness of our measure if the vast majority of deposits during the demonetization quarter were withdrawn in the first quarter of 2017 when currency notes were replenished. While this is partly true, in additional robustness tests we show that our results continue to hold when we consider the net deposit growth over the longer six month period (between end of third quarter of 2016 and first quarter of 2017) .

Our finding that districts which had higher deposit growth subsequently experienced larger increases in nighttime lights, provides a segue into the second part of the paper, where we examine the issue of redistribution both, across districts and households. First, we continue with the regional analysis, but move beyond deposit growth. Deposit growth captures a proximate measure of the intensity of demonetization. As one might suspect, districts which experienced higher deposit growth also have other pre-existing characteristics that differentiate them from ones with lower deposit growth. These districts might have been more reliant on cash, or might have low balance bank accounts making them more susceptible to money laundering. Second, much of the debate about asymmetric effects of

[4]Broadly, the maximum amount a single individual could deposit without the potential danger of further scrutiny was 250000 Indian Rupees, equivalent to 3740 US dollars on November 8th.

demonetization has centered around how the poorer/informal economy bore the brunt of the chaos that followed. Thus tracing their medium term outcomes becomes a logical extension. These reasons lead us to consider a wide range of socio-economic (SES) characteristics of districts. They include pre-demonetization measures of (a) the poverty headcount ratio, (b) the literacy rate, (c) an annualized measure of night light density prior to demonetization, (d) share of non-agricultural laborers employed in small firms (less than ten employees), (e) deposit accounts per capita, and (f) the rural share of the population. We document that districts which are poorer, or worse-off along these SES measures are the ones that experienced the largest growth in deposits during demonetization. We also show that these SES measures are *not* related to deposit growth in the months *prior* to demonetization; only after the policy takes place do poorer districts show rapid increases in deposits. For all of these too, we find comparative significant associations with nighttime lights during and after demonetization, providing evidence that the policy was redistributive.

In the second part of our section on redistribution, we complement our regional analysis, by exploring a household panel on income and expenditures. The Consumer Pyramids survey, which we describe in detail later, follows approximately 160,000 households (almost 145,000 in our sample) and records income and expenditure details, as well as other household characteristics. We divide households into quintiles based on 2015 real expenditures, and document that not only did the poorer quintiles experience larger growth in expenditures compared to the richer quintiles, we also show that these increases are consistent across a variety of goods and services. The poorer households also exhibit higher growth in real incomes, which seem to be driven mainly by increases in real wages and private transfers.

The rest of the paper is organized as follows. In the next subsection, we discuss demonetization in some more detail and the related literature. In Section 2, we discuss the various data sources and provide an overview some of the important patterns. We cover the empirical specifications and present our results on deposit growth and night lights in Section 3. Section 4 is divided in two parts. In the first part, section 4.1, we show that poorer districts saw larger percentage increases in nighttime lights, and in section 4.2, we present the household results. Section 5 concludes.

1.1 Background and Related Literature

India's demonetization has been widely covered and discussed in the media and academic blogs.[5] A reading of the Indian prime minister, Narendra Modi's, speech from November 8th, 2016, clearly indicates two rationales, corruption and terrorism, both fueled by black

[5]For a more detailed discussion of the policy, an evaluation of its effects, and some of the emerging research, see Lahiri (2020).

money.[6] The use of counterfeit notes is also mentioned in the initial announcement. Other rationales such as increasing the tax base and steering individuals towards traceable methods of transacting are not mentioned in the speech, and were enunciated later. While it is widely acknowledged that black money is a real problem in India, it is also true that most residents rely on cash for their daily activity. For example, Mazzotta et al. (2016) note that almost 87% of transactions in India used cash in 2012, and Indians with access to formal banking also tend to transact in cash and carry high denomination notes.[7] The unusual hardship that this caused the general population combined with skepticism about its success led to widespread criticism. This was validated later when in 2017, the Reserve Bank released statistics indicating that 99% of the high denomination notes made its way back to the banking system.[8]

Related Literature. Due to its contemporaneous nationwide implementation, most of the empirical literature on demonetization so far has exploited household, regional, or sectoral variations. Chodorow-Reich et al. (2020) develop a macro model which calibrates the aggregate effects. They, too, rely on district level estimates of night lights data and use elasticities from Henderson, Storeygard, and Weil (2012) to impute aggregate output reductions. To arrive at a measure of district level exposure to demonetization, however, they use confidential Reserve Bank of India data on currency note transactions. Their research finds that demonetization had negative effects during the implementation quarter on light growth, credit growth, and employment but all the effects were temporary, disappearing (or becoming insignificantly different than zero) by the first half of 2017. Beyer et al. (2018) apply different measures of district level informality - urbanization, banking access, and wage earners - and show that night lights growth was lower in informal districts during the demonetization quarter.[9]

While the preceding papers use nighttime lights, they are part of a burgeoning body of research documenting various aspects of the short run effects of demonetization. With some generalization, the literature can be categorized into two groups - those documenting short run economic and political outcomes, and those investigating behavioral changes,

[6] Modi (2016).

[7] While India's currency to GDP ratio of approximately 12% was higher than average for a sample of countries in 2014, it was not that much higher than that of the Euro Area (10.33%).

[8] As far as the tax base is concerned, taxes grew faster than GDP by 8.07 percentage points in the fiscal year of April 2017-March 2018. For comparison, the average growth difference during 2000-01 to 2009-10 was 8.32 percentage points. With regards to counterfeit notes, while there was indeed a jump in the growth of number of notes detected from 6% to 20%, the fraction that were considered counterfeit was only 0.000008% preceding demonetization.

[9] Their findings are part of a larger research project on the applicability of using night lights to measure short run variations. They also look at the 2015 earthquake in Nepal and conflict in Afghanistan.

particularly with respect to the adoption of formal banking and payment systems. Examples of the first group are Aggarwal and Narayanan (2017) (agricultural prices), Bhavnani and Copelovitch (2018) (investment projects), Khanna and Mukherjee (2020) (electoral outcomes), Karmakar and Narayanan (2019) and Wadhwa (2019) (both looking at consumption and income outcomes).[10] With respect to formalization, Agarwal et al. (2018) show that there was a significant rise in the use of digital technologies going into the first half of 2017. However, the effects are stronger for regions that already had pre-existing digital infrastructure in place. Crouzet, Gupta, and Mezzanotti (2018), show that districts with higher exposure to demonetization also exhibited a higher takeup of digital payment technologies along the intensive margin, but there were significant network externalities. Our research is quite different in both its scope and conclusions.

Apart from demonetization, our findings are relevant to the large literature on the regional and household effects of aggregate shocks including unanticipated nationwide policy shifts. Examples of regional studies include effects of the financial crisis on local employment (Mian and Sufi, 2014), and fracking on local wages and employment(Feyrer, Mansur, and Sacerdote, 2017).[11] At the household level, the literature is limited when it comes to unanticipated shocks, and even more so when it happens simultaneously across a country. Agarwal and Qian (2014) studies consumption responses to a onetime unanticipated dividend program Singapore and find large and heterogeneous effects. For every dollar received, expenditures increased by 0.80 cents over the next ten months. The response was stronger for households with lower liquid assets and credit lines. Cravino and Levchenko (2017) study the impact of Mexican peso's devaluation in 1994 on the cost of living at different points in the income distribution. They show that low-income households in Mexico continued to be adversely affected even two years later.[12] Demonetization, and more specifically our paper, is quite different in two respects. First, as a policy tool it is quite rare, and even more so when it is unannounced. Second, the policy was intended to create a negative wealth shock that would have been concentrated among the rich, and arguably

[10] Wadhwa (2019), also using the same household survey that we use in the second part of our analysis, note that poorer households experienced lower reductions in consumption relative to rich households in the months following demonetization. They attribute this to smaller reductions in utility from declining consumption in the latter group, and reliance on access to informal credit in the former group. This redistributive nature of consumption reduction reinforces our findings. In our specification, where we differentiate between the two demonetization months and the post period months, we also find that poorer households saw relative real expenditures increasing not just during the post period (Jan 2017-April 2018), but also during November and December 2016

[11] Also, see (Chodorow-Reich, 2019; Nakamura and Steinsson, 2018) summarizing the sizable emerging research on fiscal policy shocks and regional multipliers.

[12] Jappelli and Padula (2016) study an unanticipated change in severance pay policies in Italy that had large effects on lifetime resources. Also See Bunn et al. (2018) for an overview of the literature on unanticipated changes.

have reduced aggregate economic activity in both the short and medium term. However, our paper focuses on the unintended effects stemming from redistribution that went with large scale money laundering. A limitation of our research is that we cannot identify specific households that actually benefited from the cash transfers that took place during the process. Thus while our evidence is indirect- focusing on poorer regions and households, it highlights the fact that large cash transfers can lead to sizable multiplier effects on the local economy. In this respect the research reinforces some of the recent findings of sizable effects of cash transfers on the local economy. In recent work , Egger et al. (2019) show increases in aggregate output (and a positive fiscal multiplier) from randomized village-level cash transfers. Our hypothesis is effectively identical to that of Egger et al. Our "cash transfer," however, is not distributed formally through the government or an NGO. Instead, we assume an informal redistribution channel that is hard to observe, while we clearly see an increase in aggregate output.

Our paper also adds to a body of research that uses nightlight data for India to overcome the limitations of regional data which are either lacking, or of questionable quality. In addition to Chodorow-Reich et al. (2020) and Beyer et al. (2018), a number of studies have used light data to evaluate outcomes for varying geographic units - districts, villages, and electoral constituencies. Examples include Asher and Novosad (2020) on rural roads, Baskaran, Min, and Uppal (2015) on elections and electricity provision, Castelló-Climent, Chaudhary, and Mukhopadhyay (2018) on long term effects of early 20th century missionary activity on human capital, Chanda and Kabiraj (2020) on rural vs urban dimensions of convergence, Cook and Shah (2020) on the national rural employment guarantee program, and Prakash, Rockmore, and Uppal (2019) on crime in politics.

2 Data

In this section we provide an overview of the various measures and their sources both at the regional and household level. Mainly, we focus on the night time light data, our measure of deposit growth, the variables capturing socioeconomic characteristics of districts, and finally the household data from the consumer pyramid survey. Table 1 provides summary statistics of the key variables.

Night Lights Since 2012, the Earth Observation Group (EOG) has been processing and sharing global low light imaging data from the Visible Infrared Imaging Radiometer Suite (VIIRS) Day/Night Band (DNB) on a monthly basis. This supersedes the earlier annual night light data that has been widely used by economists beginning with Chen and Nordhaus (2011) and Henderson, Storeygard, and Weil (2012). One of the key advancements of the newer data, apart from the monthly frequency, is four times greater resolution (at the equator each pixel is now 0.214 sq km). Other major advancements include no saturation, lower detection limits, wider dynamic range, and 45 times smaller pixel footprints.[13] The version we use is the monthly average filtered by EOG to exclude data impacted by stray light, lightning, lunar illumination, and cloud-cover. Figure 1 portrays the path of log lights for India as whole after controlling for cloud free days and month effects. A problem that arises with monthly data, and particularly for a country like India, is that extensive cloud coverage might lead to very few or even zero daily observations for a pixel during the monsoon months. The monthly average has a non-missing value only if there was at least one day with no cloud coverage. The light extraction algorithm after removing clouds has only 84% accuracy (Elvidge et al., 2017). To deal with these issues, we control for cloud free days in our econometric work. Further, it serves as a proxy for precipitation, an important source of variation in economic activity (though we also control for monthly variation in rainfall). Despite controlling for month effects and cloud free days, one can see there is still considerable month to month variation in the data. When conducting robustness tests, we repeat our estimation but restrict the pixels to only those that were lit in the annual composite data created by EOG for 2015–i.e., by looking at an intensive margin rather than an extensive margin.[14] We aggregate (the unweighted sum) the pixel level data to the district level. The unusual spike in lights in 2017 clearly stands out in Figure 1, particularly compared to the relative stagnation preceding it.

District Level Deposit Data For our regional analysis, our primary measure of capturing the exposure to demonetization is the percentage change in total deposits between the end of the fourth quarter of 2016 and end of the third quarter of 2016. This captures deposit growth during the last quarter of 2016, of which almost two months, November and December, were what we loosely refer to as the demonetization period. The huge shortage of replacement currency in the last two months of 2016 makes deposit growth in that quarter appealing as a measure of a district's exposure to demonetization. First, it also allows us, as it were, to "follow the money". This stems from the nature of branch banking in India. As a hypothetical example, consider a migrant worker in New Delhi. Usually the worker makes monthly deposits in the Delhi branch to remit money into an account that

[13]For a more technical discussion see Elvidge et al. (2017). The EOG was previously hosted at the NOAA National Center for Environment Science, but has now moved to the Payne Institute, at Colorado School of Mines. We should note that while earlier the data was captured at around 10:30 in the night, the newer data is captured at 1 a. which could potentially weaken the correlation with economic activity.

[14]Beyer et al. (2018) and Chodorow-Reich et al. (2020) post-process the light data and remove some of these variations. Since we use lights as a dependent variable, there is no reason to make such corrections. Further, despite applying smoothing procedures, the jump in aggregate lights is clearly visible in Figure 10 of Chodorow-Reich et al.

is located in their home district. In other words, deposit growth would show up in the home district, and not Delhi. Second, contrary to expectations, 99% of the demonetized currency notes were returned. This was despite the fact that the Indian government, in an effort to punish those with unaccounted cash, introduced additional rules regarding the amount of discontinued currency that could be deposited into a bank account.[15] Those who had undisclosed currency clearly figured out ways to launder their cash. These methods, which emerged quickly and were widespread, included channeling currency notes through accounts of employees, brokers who found low income households or zero balance account holders, advance salary payments to employees, settlement of debts, or even finding businesses (usually informal) who were willing to sell goods at a markup if purchased with the defunct notes. Invariably, all of these methods involved paying premiums or commissions to the intermediaries and ultimate depositors.[16] Irrespective of whether currency notes were deposited within the same district, or redirected into adjoining districts or, as we shall note later, even across the country, deposit growth captures where it ended up going. To summarize, even though the vast majority of deposit growth undoubtedly reflected cash shortage, it also helps us examine the economic activity of regions where the money was finally deposited.

This data is publicly available from the Reserve Bank's website.[17] Since the Reserve Bank publishes total deposits, the percentage change is the net growth in deposits. If an account holder deposited a certain amount in old currency and replaced it with new currency, the growth in deposits would be zero. In reality, due to the severe restrictions in place, the amount of currency in circulation during those two months fell dramatically to almost half of its pre-demonetization, leading to large variations in deposit growth across districts.[18]

In our econometric analysis, we use this raw deposit growth measure. The mean value across districts during that quarter was almost 14% with a standard deviation of 7%. This stands in sharp contrast to preceding five years when the mean growth was 1.8% with a standard deviation of only 2.5% for the same quarter. Figure 2 displays the time series of the unweighted mean of the district deposit growth after subtracting the five year (2011-15) average for that district-quarter.[19] Figure 3 provides a glimpse of the spatial

[15]Broadly, the maximum amount a single individual could deposit without the potential danger of further scrutiny was 250000 Indian Rupees, equivalent to 3740 US dollars on November 8th.

[16]See KPMG (2016) and Rajagopalan (2020) for a description of these methods.

[17]Statement 4A of the Quarterly Statistics on Deposits and Credit of Scheduled Commercial Banks. Total deposits usually reflect values for the last day of the quarter.

[18]Initially, daily cash withdrawals were restricted to INR 10,000 (US$150) per day with a weekly limit of 20,000.

[19]For each district-quarter we calculate: $\ln\left(\frac{deposit_{y,q}}{deposit_{y,q-1}}\right) - \frac{1}{5}\sum_{y=2011}^{2015} \ln\left(\frac{deposit_{y,q}}{deposit_{y,q-1}}\right)$.

variation of the same growth rate for the demonetization quarter. At the upper end of the distribution, there were many districts recording more than 30% growth in deposits. An unusually large share of these belong to the northeast states of India, particularly, Nagaland and Manipur. This should not come as a surprise for those closely following developments in India during that time. The news media reported that the area has many districts that are officially "scheduled tribes" designated populations who benefit from income tax exemptions. This made them an important conduit for money laundering with reports of chartered planes flying in with cash from districts close to New Delhi. A second possibility is that the undeclared cash being used by separatist groups that operate in this area made its way back to the banks.[20] Other than the northeast, one can see another bunching of districts in the north central and north-west part of the country. This includes the state of Rajasthan, western portions of Uttar Pradesh, and western districts of Madhya Pradesh. Not surprisingly, the southern states exhibit low deposit growth. Lastly, a cluster of poor districts in east-central area (Eastern Uttar Pradesh, Bihar, Jharkhand, Chattisgarh) exhibit low or average deposit growth.

There are at least a dozen districts that experienced declines during that time period. These are concentrated in metropolitan areas. Particularly striking are Mumbai (-16%) and Suburban Mumbai (-2%). Chennai also experienced a decline of -0.4%. More generally, at the lower end of the distribution we see a predominance of major urban areas such as Bangalore, Delhi, Hyderabad, Kolkata, etc. The fact that these are all urban areas could mean that there was less dependence on cash to begin with. It is also possible that a large chunk of the undeclared cash was redirected to adjoining rural districts or to other parts of the country. Nevertheless, neither of these can completely account for a *decline* in total deposits during those three months. It is likely that Reserve Bank was more responsive, consciously or not, to the cash needs in these places which facilitated greater withdrawals compared to the rest of the country.

Figure 2 also indicates that the rapid growth in deposits in the fourth quarter was largely, but not completely, reversed in the first quarter of 2017 as more liquidity flowed into the economy. We show that our results remain robust if we use instead the growth in total deposits between end of the third quarter of 2016 and end of the first quarter of 2017.[21] While we use deposit growth, others such as Chodorow-Reich et al. (2020) have used confidential data to create a measure of note shortage, while Crouzet, Gupta, and

[20]See Sen (2016) on chartered planes flying to Nagaland. Loiwal (2016) reports on effects of insurgency outfits. Interestingly, there is no unusual growth in deposits in the Kashmir region.

[21]We chose not to focus on the longer deposit growth because withdrawals in the first quarter of 2017 could be driven by factors other than simply replenishing cash for daily use. These could include behavioral changes (formalization) and withdrawal of "redistributed" deposits by recipients to finance expenditures. However, we do conduct some robustness analysis in the appendix.

Mezzanotti (2018) use a combination of deposit growth and the location of currency chests in banks to create a measure of note shortage. For most places, note shortage and deposit growth are likely to be highly correlated. However, we should reiterate that the purpose of our paper is not to measure the former, but to follow where the money ended up.[22]

Data on other district level characteristics We use the 2011 census data to calculate district level measures for the literacy rate and the rural share of the population. Our measures of the headcount ratio are taken from Alkire, Oldiges, and Kanagaratnam (2018), who in turn use the 4th National Family Health Surveys conducted in 2014-15. The survey is representative at the district level. For the measure of night lights prior to demonetization we use the 2015 annualized version of the VIIRS data. For the share of non-agricultural laborers employed in small firms, we use the sixth economic census conducted in 2013-14. We define firms that have less than ten workers (hired and owners) as small firms.[23] The data for deposit accounts per capita in 2014 comes from the Reserve Bank of India.

Household Data While we first focus on district level outcomes, redistribution may also happen at the household level within districts. Therefore, we also look at household incomes and expenditures. We use Consumer Pyramids, a proprietary panel survey published by the Centre for Monitoring Indian Economy (CMIE). The survey follows almost 160,000 households since 2015 and is designed to provide an overview of incomes, expenditures, assets, demographics and more recently, employment and sentiments and is representative at the national level.[24] Households are interviewed tri-annually about their economic situation over the previous four months. Even though India is about 30% urban and 70% rural, the survey is flipped in that 70% of the respondents are urban and 30% rural. The rationale is that there is greater heterogeneity in urban than in rural households. We use the survey data to see if household income and expenditures were differentially affected post-demonetization. Figure 4 displays the logarithm of the weighted mean of household real income and real expenditures based on the survey. Even here, there is a clear increase

[22] Currency chests are located at approximately 4100 bank branches across the country spanning all districts. As the name suggests, they are equipped to handle cash management. About 94% of them are located in government owned banks, with two-thirds in branches of the State Bank of India and its affiliates. Another 27% are in other nationalized banks.

[23] The economic census, which surveyed 58.5 million firms, excludes establishments that engage in crop production and plantation (i.e. most of the agricultural sector), and public services. However, it includes allied agricultural activities and also government owned production units. Firms may be registered or unregistered.

[24] To get real measures of income and expenditures, nominal measures from the Consumer Pyramids are deflated by state-level, rural/urban measures of CPI from the Consumer Price Indices Warehouse provided by the Government of India. We use the most recent, general data (2012 base), which can be found here: http://164.100.34.62:8080/.

in the slope around the time of demonetization.

3 Empirical Specification and Regional Results

We begin our analysis by looking at the district level variation covering the period from January 2015 to April 2018. The starting month is chosen so as to be consistent with data availability for the household level analysis in section 4.2. Additionally, it provides a reasonable balance between the length of pre and post periods. We are able to create consistent data for 625 of the 640 districts in the 2011 census.[25]

3.1 Preliminary Analysis: Testing for Parallel Trends

The first step of our analysis is to establish that the growth in deposits between quarters 3 and 4 of 2016 (referred to as "demonetization-centered deposit growth") is not related to pre-trends in nighttime lights. We show this absence of differential pre-trends in an event figure. Figure 5 plots the monthly β_t from the following estimating equation, using (i.e., omitting) October of 2016 as the base month:

$$\ln Lights_{it} = \alpha + \sum_{t=Jan.2015}^{April2018} \beta_t Month_t \times DG_i^{2016q3-q4} + \beta'_{\mathbf{X}}\mathbf{X_i} + \gamma_i + \gamma_{st} + \epsilon_{it} \qquad (1)$$

Equation (1) tests for differential monthly effects of demonetization-centered deposit growth on nighttime lights relative to the month prior to demonetization, using our baseline specification that includes district and state-year-month FE and controls for cloud free days, population, and district geo-climatic differences.[26] In other words, if demonetization-centered deposit growth is accounting *only* for differences in the effect of demonetization as we hypothesize, then there should be no consistently estimated effect of 2016q3-2016q4 deposit growth on nighttime lights prior to demonetization. Indeed, monthly effects of demonetization-centered deposit growth in Figure 5 show a noisy, but inconsistent association with nighttime lights prior to demonetization.

Following demonetization in November 2016, however, two patterns emerge. First, districts that exhibited larger deposit growth during demonetization, or districts that we interpret to have been more exposed to demonetization, have relative declines in nighttime

[25]The Reserve Bank of India updates its tables periodically following the formation of new districts. We lose some districts that were split after the 2011 census for which no clear parent district could be assigned. Additionally, the Bank does not collect data individually for the nine districts of Delhi. As a result, Delhi, and also the union territories of Chandigarh and Dadra and Nagar Haveli are automatically dropped during estimation since they have no within region variation.

[26]The specification of Figure 5 follows that of col. (5) of Table 2. Coefficients from Equation (1), which are shown in Figure 5, are similar when including only district and state-year-month FE.

lights in the months during and immediately after demonetization.[27] After this initial decline, however, these districts that were more exposed to demonetization show relative increases in nighttime lights. Monthly coefficients of 2016q3-2016q4 deposit growth for the post-demonetization period are consistently positive, statistically significant, and larger in magnitude than in any month during the noisy pre-period, suggesting a clear break from the macroeconomic shock under study. We next study these during- and post-demonetization effects through difference-in-differences analysis.

3.2 Short and Medium Term Impacts of Demonetization

Our baseline analysis explores the relative within-district aggregate impacts of demonetization using nighttime lights. To do so, we estimate district-level difference-in-differences (DD) in nighttime lights from variation in the pre/post quarterly change in deposits following the enactment of demonetization in November of 2016. This is given formally by the following estimating equation:

$$\begin{aligned} \ln Lights_{it} = \alpha + \beta_D I_{During} \times DG_i^{2016q3-q4} + \beta_P I_{Post} \times DG_i^{2016q3-q4} \\ + \beta'_{\mathbf{X}} \mathbf{X_i} + \gamma_i + \gamma_{st} + \epsilon_{it} \end{aligned} \tag{2}$$

The base district panel is monthly (t), running from January 2015 to April 2018, and is comprised of 625 (i) districts. District (γ_i) and state-year-month (γ_{st}) are included in all specifications, suggesting our coefficient is capturing state-specific within-district variation over time.[28] Our coefficients of interest β_D and β_P measure the differential change to night time lights during and post demonetization by relative exposure to demonetization–measured by the influx in deposits due to demonetization ($DG_i^{2016q3-q4}$). We separately estimate the immediate effect of demonetization (November and December of 2016) to account for initial disruptions due to the large reductions in currency and its impacts on transactions. Since note shortage and deposit growth are likely to be correlated (Chodorow-Reich et al., 2020), we hypothesize $\beta_D < 0$, but in general remain agnostic to the sign, significance, and magnitude of this coefficient. As argued in the introduction, the raw aggregate data portray not only the absence of negative economic effects, but a consistent positive effect. Therefore, and more crucial to our analysis, we hypothesize $\beta_P > 0$. The dual inclusion of during and post interactions implies their coefficients are accounting for the relative effect of demonetization compared to the pre-period of January 2015 to October

[27] The during demonetization decline, however, is similar in magnitude to pre-demonetization declines, suggesting a potentially spurious immediate decline in nighttime lights following demonetization.

[28] Our results are not dependent on using state-year-month FE. When using year-month FconnE, the post-demonetization increases associated with demonetization-centered deposit growth remains roughly similar in magnitude and statistical significance.

2016.

Table 2 formally tests this idea by estimating our base DD equation given by equation (2). All estimations include district and state-year-month fixed effects, and standard errors are clustered at the district level.[29] Column (1) estimates the DD bivariate equation, omitting other controls. Columns (2)-(5) include the natural log of cloud free days. Since lights are strongly correlated with population, column (3) includes the district-level population (2011 Census). Our final set of controls comprises a large range of district-level geoclimatic conditions that are piecemeal included in column (4); these include the average and standard deviations for land area, temperature, precipitation, malaria ecology, ruggedness, agricultural land suitability, the average distance to the coast, and indicators for biomes.[30] Both the population controls of column (3) and the geoclimatic controls of column (4) are time invariant, so to include them in our within-district estimations, we interact all controls with a during-demonetization indicator and a post-demonetization indicator; this is identical to how our regressor of interest (deposit growth Q3-Q4, 2016) is treated. Doing so allows us to control for differential post-demonetization trends that may be correlated with 2016q3-2016q4 deposit growth. Beyond these variables, it is well known that fluctuations in rainfall has important effects on economic activity in India. Therefore, in column (4) we also control for log monthly rainfall, which is time variant.[31] All controls are included in column (5).

For all specifications of Table 2, a clear pattern exists: there is a statistically significant ($p < 0.01$) negative relationship between night time lights and demonetization-centered deposit growth in the immediate months during demonetization, but this initial negative relationship is offset by a rebounding statistically significant ($p < 0.01$) positive effect throughout 2017 and early 2018. From the simple estimation of column (1) to our full baseline model of column (5), there is very little variation in the significance of our main coefficients. Magnitudes are slightly attenuated in column (3) when separately controlling for the pre-period level of population, but the estimated effects remain statistically significant at the 1% level. Using the estimates from column (5), a standard deviation increase in a district's deposit growth from demonetization (s.d.=0.075) is associated with an av-

[29]Table 2 also includes within district spatially adjusted standard errors for 30km (in brackets, "[ ]") and 200km (in braces, "{ }") (Fetzer, 2019; Hsiang, 2010). Given the close similarity between the district-clustered standard errors and the standard errors with spatial adjustments, we simply report district-clustered standard errors after Table 2.

[30]All geographic variables are taken from Chanda and Kabiraj (2020), except for the biome indicators which are calculated from Henderson et al. (2018).

[31]The monthly rainfall data was webscraped from the Indian Meteorological Department website. About 5% of the sample (district-month) were missing observations. For those that were located in large states, we used the average of adjoining districts for that month. For districts located in smaller states, we used the state mean for that month (Jammu and Kashmir, Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, and Sikkim).

erage monthly decrease of 2.4% in nighttime lights during demonetization (i.e., November and December 2016), and an average monthly increase of 4.2% from January 2017 to May 2018.[32] Since lights by themselves are difficult to interpret, one can use estimated measures of elasticity between lights and GDP. Hu and Yao (2019) estimate the elasticity of GDP per capita with respect to VIIRS nighttime lights to be in the 0.8-1 range for India. In other words, a one standard deviation increase in deposit growth is associated with a 3.4 to 4.2 percentage point increase in GDP per capita in the post demonetization period.[33]

3.3 Placebo Tests and Robustness

Alternative Timing We next show that our measure of intensity–the growth rate of deposits centered around demonetization–is indeed accounting for district level exposure to demonetization. To do so, we alternate both the treatment date of demonetization and look at potential effects from the quarterly change in deposits in other periods.

Table 3 re-estimates our baseline findings of Table 2 but shifts the treatment date one year early to November of 2015. This shift generally causes all significant estimates to dissipate. The decline during demonetization in Table 3 is now estimated to be close to zero and is statistically insignificant in all specifications. The same holds true for the previously estimated post-December increase, which is now negative and statistically insignificant for all specifications. Given that demonetization is considered to be a true macroeconomic shock, it is no surprise that the true date of the treatment is associated with changes to nighttime lights.

Alternative Intensity In addition to confirming the treatment date, Figure 6 shows that it is indeed the change in deposits around demonetization that is driving our results. Figure 6 plots the during-demonetization (subfigure a) and the post-demonetization coefficients (subfigure b) by each quarterly growth rate of deposits. That is, we re-estimate equation (2) substituting the quarterly deposit growth around demonetization (2016q3-2016q4) with all other quarterly changes to deposits.[34]

For the during-demonetization interaction, the quarterly change in deposits one year prior to demonetization (2015q3-2015q4) also has a statistically significant negative effect on nighttime lights, suggesting a potential alternative channel between deposit growth in

[32] Effects are relative to the pre-period.

[33] More specifically, their estimates of 0.8 and 1 are for countries with GDP per capita (constant 2011 international dollars) of $5000 and $10,000 respectively. Commonly referred estimates such as those of Henderson, Storeygard, and Weil (2012) and Pinkovskiy and Sala-i Martin (2016) are based on the older DMSP satellite program and have a lower elasticity of 0.3. That would imply a lower increase of 1.3%. However, the satellites used an entirely different measurement scale.

[34] The estimated coefficients follow the specification of column (5) of Table 2.

quarters 3 and 4 and the decline in nighttime lights immediately following demonetization. With this in mind, we next control for average quarterly deposit growth and deposit growth one year and one quarter prior to demonetization in Table 4. The inclusion of early deposit growth measures does not alter the estimated effect of demonetization-centered deposit growth found in Table 2. For the post-demonetization increase, however, the only quarterly change in deposits that has a positive and statistically significant association with nighttime lights is the change centered around demonetization, providing further evidence that our use of deposit growth rates from demonetization are indeed measuring (at least in part) the intensity of demonetization. In Section 4.1 we further explore the importance of district specific characteristics in their exposure to demonetization.

Robustness to Pretrends Table 4 controls for a number of potential trends in the pre-period (January 2015-October 2016); specifically, the *average* pre-period quarter-to-quarter percent change in deposits (col. 1 and 3-4), the average growth of nighttime lights (col. 2-4), and the growth of deposits one quarter (2016q2-2016q3) and one year (2015q3-2015q4) prior to demonetization (col. 4). All estimations include the baseline set of controls given by column (5) of Table 2.

Some districts may be subject to either more variation in quarter-to-quarter deposit growth or may be more vulnerable to changes in deposits that could potentially lead to a spurious association with post-demonetization increases in nighttime lights. Therefore, we control for the average quarter-to-quarter growth of deposits in column (1). The inclusion of average deposit growth does not substantially affect our coefficients of interest, again suggesting that our baseline measure of deposit growth is capturing differential effects from demonetization.

Although pre-trends in nighttime lights appear to be absent in Figure 5, we also control for the post-demonetization change in nighttime lights associated with pre-demonetization trends to show that our main finding is independent of ongoing trends in night-time lights. To do so, column (2) controls for during/post-demonetization indicators interacted with the average monthly district-level growth rate in lights from January 2015-October 2016. The inclusion of this control leads to a slight attenuation in the effects both during and after demonetization, with the during-demonetization decline becoming statistically indistinguishable from zero. The post-demonetization increase in nighttime lights, however, remains both positive and statistically significant.

Column (3) includes both the pre-period average growth rate of lights and deposits. The joint inclusion of these controls does not alter the estimated post-demonetization increase, further suggesting that our spatial measure of intensity is not being driven by pre-period trends in either our outcome or regressor of interest.

While Figure 6 shows that no other quarter-to-quarter growth rate is associated with the post-demonetization increase in nighttime lights, we take this one step further by controlling for the quarterly change in deposits one quarter and one year early in column (4) of Table 4. The inclusion of additional quarterly deposit growth measures does not alter the coefficient of demonetization-centered deposit growth.

Additional Robustness Checks We perform a number of additional robustness checks that follow the format of Table 2. These tables are found in the appendix section A. To quickly summarize: (1) we extend the sample period back to 2014 in Table A.2; (2) we mask the nighttime lights measure by whether lights were present in 2015, thereby testing the extensive margin in Table A.3; (3) since a large fraction of the deposits were withdrawn in the first quarter of 2017, we examine the relationship between nighttime lights and deposit growth one quarter longer (2017q1) in Table A.4; (4) in place of the log of nighttime lights, we examine the monthly growth rate (or the log difference) in Table A.5; (5) we also examine the growth rate with the longer growth rate of deposits of Table A.4 in Table A.7, and (6) re-estimate our base results with the growth rate of the masked light data in Table A.6. For all specifications, a statistically significant positive post-demonetization effect is estimated, providing further support our baseline findings of Table 2.[35]

4 Redistribution

Having established that districts with higher deposit growth exhibited faster growth in nighttime lights, we now move to the issue of redistribution. In the first part we continue examining district-level differences, and show that deposit growth during the demonetization quarter was also correlated with a variety of socio-economic indicators, all of which are also associated with subsequent growth in lights. In other words, it is the poorer districts that seem to have exhibited faster growth in lights post-demonetization. In the second part, we move beyond districts and look at household survey data. We show that, poorer households recorded larger increases in expenditures and income post-demonetization.

We previously noted that following demonetization lights show an unusual spike, the official growth rate of real GDP has a small decline, and the consumer household survey shows a continuous increase in real incomes and expenditures. All of this is certainly consistent without any concurrent redistribution. Nevertheless, as we observed, urban areas

[35] In addition to the above, we re-estimated our specification by (a) dropping districts that higher than 25% growth in deposits, and (b) the state of Uttar Pradesh which exhibits unusual light behavior (Chodorow-Reich et al., 2020). We also considered the growth rate of smoothed lights used by Chodorow-Reich et al. (2020) and Beyer et al. (2018). Though the sample is shorter, we still get the positive effect for the post demonetization period but no negative effect for the during period.

were the ones that recorded lower deposit growth. Furthermore, money laundering involved large scale redirecting of cash through various mechanisms with 99% of the discontinued currency being returned. Whether black money was rerouted through brokers who used people with low bank balance accounts, or advance payments of wages, or through employees, or through settlements of unpaid debts, it invariably involved poorer households being beneficiaries.[36] In effect, what potentially transpired was a one time widespread reallocation or redistribution of wealth, but not the kind the government had in mind.[37]

An obvious question that follows is whether the potential redistribution through such channels could be sizable enough to actually have any expansionary effect. An accurate calculation would require knowledge regarding the amount of unaccounted cash in the country preceding demonetization - still very much an unknown. While there is no smoking gun, we can make a calculated guess. In an update to their earlier widely cited studies, Medina and Schneider (2018) estimate India's shadow economy to be on average almost 25% of GDP for the period 2004 to 2015. Assuming that the cash-GDP ratio in the shadow economy is the same as that of the regular economy, i.e. 12%, unaccounted cash would amount to approximately 3% of GDP.[38] If approximately 30% was redistributed during the money laundering process, this amounts to 1% of GDP. As a point of reference, refundable tax credits and assistance to households in 2010 as part of the American Recovery and Reinvestment Act (ARRA) stood at 0.36% of GDP. Thus, even if only 10% was redistributed, the relative value would be similar to ARRA rebates.[39]

While it is plausible that the laundering process created an expansionary effect, we should add two qualifications. First, unlike a regular stimulus, this would not benefit all regions equally. It would be a function of broker networks, distance to major urban centers, regions that benefit from special tax exemption policies, etc. Second, not all black money was laundered through rural areas. Given the large number of urban poor, deposits were also

[36]In situations where someone received a fee for depositing the money, the remaining amount was usually returned during that quarter or the next depending on currency availability. During that time the government also introduced certain schemes for declaring black money, but these were subject to tax rates of 45-50%, which would likely be the de facto maximum "fee" for any money laundering method. First hand anecdotes indicate that the going rate could be as high as 40% of the amount being deposited.

[37]The government counted on a substantial fraction of notes never being returned leading to a reduction in liabilities of the Reserve Bank. Bhagwati, Dehejia, and Krishna (2017) and Koning (2017) are early essays speculating on unintended redistribution.

[38]These numbers are conservative. We obtained an unreleased government sponsored report in 2013 titled "Study on Unaccounted Incomes in India" prepared by the National Institute of Public Finance and Policy. They estimate that the shadow economy was about 45% of GDP (Table 4.16) for 2000-2010. The money to GDP ratio in the shadow economy is also certainly higher than our assumption of 12% since the formal banking sector is avoided for these transactions.

[39]Bhagwati, Dehejia, and Krishna (2017) also view 30% as the eventual equilibrium laundering fee. The numbers for ARRA reflect the sum of outlays for Title 1 (Tax Provisions) and Title 2(Assistance for Unemployed Workers and Struggling Families) in Congressional Budget Office (2009).

laundered locally.[40] A district level analysis would not uncover the latter. In this respect, the household analysis in the second part of this section, especially when we incorporate district fixed effects, further reinforces our initial regional findings of redistribution.

Laundering is not the only way redistribution might happen. As mentioned in the introduction, the role of messaging and policy uncertainty could have also played a role. First, a large section of the population, particularly the poor and the middle class, viewed this policy, favorably, and this could have made them more optimistic about the country's growth prospects, leading to higher expenditures. Second, even though those with black money managed to figure ways out to launder it, the policy may have created uncertainty regarding future policy actions leading them to be more cautious about their expenditures. While technically not redistribution, these effects would lead to relatively larger increases in expenditures at the lower end of the income distribution, and lower increases at the higher end over the medium term. This provides further rationale for our two pronged strategy of looking both at regional and household effects.

Apart from these one must also entertain (i) the role of formalization, and (ii) increases in credit due to deposit growth. Both of these could lead to an expansion in economic activity in poorer areas. In theory, populations in poorer regions, and those in lower income groups might be more likely to formalize. However, some of the emerging research seems to indicate that while formalization did increase, it was dependent on pre-existing fintech infrastructure.[41]

With respect to credit, we report our investigations in section C of the appendix. We used quarterly data available from the Reserve Bank. Using a similar specification as those in our baseline estimates, indeed we find that districts which recorded higher deposit growth, also experienced subsequent increases in credit. However, the event figures indicate that credit in those districts were growing already.[42] This is not surprising since the government has numerous policies in place to encourage credit to poorer districts.

[40] While it might be easier to launder locally, one can conjecture that those with unusually large amounts (more to hide) would prefer to avoid local channels. Nevertheless on the margin, there would be some redistribution locally as well. Furthermore, this within district redistribution could just as well apply to rural districts.

[41] See Agarwal et al. (2018) and Crouzet, Gupta, and Mezzanotti (2018). The household survey we use provides information on access to banking, but 95.7% of the sample, in the wave prior to demonetization, already owned an account.

[42] Figures C.1 and C.2 in the appendix. Given that substantial portions of the initial deposits were withdrawn the next quarter, we do the analysis for both (a) deposit growth in the 4th quarter of 2016, and (b) over the six month period of q4, 2016 and q1,2017. The results are similar.

4.1 Regional Analysis

We begin our district level analysis by first examining the association between district characteristics with demonetization-led deposit growth. In short, we find that poorer, or more backwards, districts had larger deposit growth on average from demonetization. This finding is supported by a cross-district analysis that regresses demonetization-led deposit growth on a number of district aggregates associated with pre-demonetization poverty, education, and income. Specifically, we look at the association between a district's deposit growth and the district's poverty headcount ratio, literacy rate, pre-demonetization nightlight density, share of employment in small non-agricultural firms (i.e., less than 10 employees), deposit accounts per capita, and rural population share. These measures, as should be apparent, are quite generic in terms of capturing differences in living standards.

Table 5 displays the cross-district estimates of regressing demonetization-led deposit growth. All columns include state fixed effects and the set of geoclimatic controls, and all regressors are standardized to a mean of 0 and standard deviation of 1 for ease in interpretation. The regressor of interest in column (1) is the 2014-15 poverty headcount ratio (Alkire, Oldiges, and Kanagaratnam, 2018). The positive and statistically significant coefficient shows that districts with more poverty experienced larger deposit growth. Column (2) replaces the poverty ratio with literacy rates from the 2011 census. The coefficient remains roughly similar in magnitude but changes sign to reflect that less literate districts are the ones that had larger changes to deposits. Column (3) considers the pre-demonetization log light density from 2015. If lights are indeed a good proxy of output, then having a lower density of lights prior to demonetization is consistent with lessened output associated with poorer districts. Indeed, a standard deviation increase in pre-demonetization nightlights has a similar effect as the literacy rate in column (2): districts with a lower density of nightlights have greater deposit growth from demonetization. Column (4) considers the 2013-14 share of workers employed in small firms in the non-agricultural sector, which intends to proxy informal non-agricultural employment. With that in mind, a greater share in small firms, or in the informal sector, is positively associated with deposit growth. Column (5) replaces the share of workers in small firms with the log of deposit accounts per capita in 2014. The variable is intended to capture pre-demonetization financial inclusion. The coefficient is negative, and also has the highest magnitude. This is to be expected since the places with fewer deposit accounts were likely to be the more cash reliant.[43] Finally, column (6) considers the rural share of the populations. The coefficient from column (6)

[43] We use the March 2014 measure since it precedes the massive push to financial inclusion initiated by the government from August 2014. We get similar results for March, 2016. Unlike deposit data, account penetration data is published annually. For an assessment of the government's financial inclusion project, see Agarwal et al. (2017). As an aside, deposit growth during the demonetization quarter is more strongly correlated with account growth between 03/14-03/16 than that of 03/16-03/17.

again confirms that the growth in deposits from demonetization is happening primarily in rural, poorer, and more informal districts.[44] In summary, all measures have the expected signs, are statistically significantly associated with demonetization-led deposit growth, and effects are similar in magnitude, with a one s.d. increase in each being associated with a 2-3 percentage point change in the rate of deposit growth.

Given the consistent findings of Table 5, it is possible that poorer districts generally have larger percentage point changes in their deposits, such that the effects of demonetization are simply more pronounced there. Table 6 shows that this is not the case. Instead of the deposit growth from demonetization, Table 6 regresses the average quarterly deposit growth from 2014q1-2016q3. When using this pre-period mean of quarterly deposit growth, all previously significant measures dissipate, and the magnitude of the effect of each poverty/informal measure is estimated to be close to zero. The estimates of Table 6 suggest that poorer districts had larger percentage point changes in deposits from demonetization, not that these poorer districts have larger on average deposit growth.[45]

Finally, to further show that the estimated effect of demonetization-led deposit growth is a product of these underlying district characteristics, Figure 7 replaces the monthly estimated effect of deposit growth (relative to Oct. 2016) with the monthly estimated effect for each proxy of district poverty/informality. As seen, effects are very similar to those of deposit growth. For literacy, nightlights, and accounts per capita, which have a negative association with deposit growth from demonetization, the opposite estimated effects are seen: districts with high values, have positive relative coefficients during demonetization followed by relative negative coefficients in the post period.

4.2 Household Analysis

Given that poorer districts are driving our regional results, it is of interest to see whether this aggregate association is also reflected in underlying micro data. The most direct examination is to look at real expenditures and income of poorer households relative to the richer ones. Prior literature has shown larger responses (i.e. marginal propensities to consume) for poorer or more constrained households (Agarwal, Liu, and Souleles, 2007; Jappelli and Pistaferri, 2014, 2019; Parker, 2017). Of these, only, Jappelli and Pistaferri (2014) consider unexpected income shocks. Unlike these household studies, we have no clear way to identify which households might have received an income shock. Thus, like in

[44]By definition, almost 100% of agriculture is informal, whereas about 72% of non-agriculture was informal in 2004-05 National Commission for Enterprises in the Unorganised Sector (NCEUS) (2009). In an earlier draft, we considered the agricultural labor force share as well, with similar results.

[45]To reassure ourselves, we repeated this exercise using the fourth quarter average deposit growth from the preceding five years as the dependent variable. It was not significantly associated with any of our district characteristics.

the regional analysis, we focus on the timing of the aggregate shock, and examine the more general question of changes in relative expenditures and incomes between different groups.

The data that we use, Consumer Pyramids, is a panel survey of approximately 160,000 households, conducted in three waves during the year.[46] Each household is surveyed once during a wave, and is asked to provide information on various categories of income and expenditures for each of the preceding four months, in addition to household demographics. We deflate the measurements using state level- rural and urban CPI data. To maximize coverage, we use an unbalanced panel.

Average monthly expenditures during 2015, i.e. a year or more prior to demonetization in November 2016 are used to create quintiles. Within-household differences in expenditure and income during (Nov. and Dec. 2016) and after (Jan. 2017-April 2018) demonetization are then compared between the lower four quintiles relative to the top quintile (i.e., the omitted quintile). Means by quintile for the natural log of real expenditures are given in Figure 8. The graph indicates relatively stagnant expenditure profiles for all the quintiles (with the exception of a hump shaped pattern for the richest) preceding demonetization. Almost immediately after the event, there is an upward trend for all groups.[47] Summary statistics are provided in Table 7. We display means for the entire period of study, and also the pre, during and post-demonetization periods. One can see that even during demonetization, there is some increase in mean expenditures for the two lowest quintiles, while the other groups experience declines. Post-demonetization, all quintiles show increases in the figure. In the summary statistics, the richest show a decline too, but that is likely a function of averaging (and the fact that a peak was reached during mid 2015). It also appears as though the lowest quintile experiences a larger relative post-demonetization increase. The lower half of the Table also provides income information for each of the quintiles.

To formally test the, we estimate the following equation:

$$\ln y_{it} = \sum_{q_i=1}^{4} \beta_{q_i} I_{during} \times I[q_i] + \sum_{q_i=1}^{4} \beta_{q_i} I_{post} \times I[q_i] + \beta'_{\mathbf{X}} \mathbf{X_i} + \gamma_i + \gamma_t + \epsilon it \tag{3}$$

Our outcome of interest is monthly (t) real expenditures for i households (N= 144,117).[48] Using 2015 means of real expenditures, households are divided into quintile indicators. In

[46] The proprietary survey is conducted by Center for Monitoring Indian Economy (CMIE), a private company which is also well known in the research sphere for their Prowess® database of financials of Indian companies. Given the absence of other household level data sources, it is no surprise that many of the research papers on short run effects of demonetization have also relied on Consumer Pyramids for some, or all of their analysis.

[47] Unlike Figure 4 which uses national level weights, the ones lines here are simple means within groups.

[48] While there are a total of 144,117 households in our data, the unbalanced panel implies not all households are present in each month. The number of households ranges from 108,912 (July 2017) to 129,280 (December 2015). Restricting our analysis to a fully balanced panel yields similar results.

other words, if household i is in the bottom 20% of initial (2015) real expenditures, $I[1] = 1$; if household i is in the 20th-40th percentile of either initial measure, then $I[2] = 1$; etc. We estimate coefficients for the bottom 4 quintiles relative to the top quintile (the omitted, or base, group) during demonetization ($I_{during} = 1$ for November and December of 2016) and following demonetization ($I_{post} = 1$ for January 2017-April 2018).[49] Time invariant household characteristics are also interacted with during and post indicators; these include an indicator for rural households, the average years of schooling among adults within the household, the average age of all household members, the number of school-age children in the household, and indicators for religion and caste. We define adults as those members of the household 25 and older. The number of school-age children is defined as a count of household members under 16 years of age. Household fixed effects are included in all regressions (γ_i), and we sequentially consider year-month, year-month by state, and year-month by district fixed effects (γ_t). Standard errors are clustered at the district level for all estimations.

Expenditures Table 8 displays our base household quintile estimations. Columns (1)-(3) respectively change time period fixed effects from simple year-month to year-month by state and year-month by district. Column (4) includes a number of family size fixed effects and fixed effects for the number of months distant from the interview month to the estimates of column (3).[50] Finally, column (5) adds a number of static household characteristics (measured the wave prior to demonetization and interacted with during- and post-demonetization indicators).[51] All coefficients on the lower 4 quintiles are positive and significant at the 1% level both during and after demonetization. The magnitudes are also stable across each specification and estimated differences between quintiles are statistically significant. This suggests that *relative* to the top quintile, the lower quintiles had gains in expenditures during and after demonetization. The during demonetization effect, however, is somewhat misleading. As noted earlier the lowest quintiles had increases in expenditures, while the higher quintiles had decreases. Therefore, the positive during demonetization coefficients of Table 8 are accounting for relative increases or smaller relative declines among the four lower quintiles compared to that of the top quintile. In contrast, there is a clear increase in expenditures following demonetization, and this increase is relatively larger for

[49] Appendix D considers an alternative specification in which the middle three quintiles comprise the omitted group.

[50] As discussed, households are interviewed once every 4 months (rolling) and asked about past monthly income and expenditures. Distance from the interview month FE intend to capture general errors in recollection. Family size fixed effects include indicators for both family size and earning members.

[51] As stated earlier, the household characteristics include an indicator for rural households, the household's years of schooling, the household's mean age, the number of children in the household, and indicators for religion and caste.

those households that initially had lower expenditures. As one moves from column (1) to (5), the relative increases become larger in magnitude. Compared to their pre-demonetization values, the poorest quintile experienced a 40% increase in expenditures relative to the rich. While the addition of numerous fixed effects, leads to more precise estimates, one might also be worried about over controlling. However, even the parsimonious specification in column (1) suggests a 20% increase in relative expenditures. Furthermore, the magnitude increases for the lower quintiles–i.e., the effect for quintile 1 is statistically larger than quintile 2, which in turn in statistically larger than that for quintile 3, etc. In other words, relative to the top quintile, poorer households are increasing their expenditures more than richer households. This finding, while not definitive, is suggestive of some redistributive effect from richer to poorer households. We should also note that, even though we do not distinguish between rural and urban areas, the composition of the quintiles reflect underlying differences. While the first quintile is evenly divided between rural and urban households, the fifth has less than 10% from rural areas. As with our regional analysis, we also check that the relative increases in expenditures are tied to demonetization and not before that. Figure 9, provides support for that. While there is some indication that poorer households might have experienced higher expenditures a couple of months before demonetization, the overall consistency during and post demonetization is quite evident.

Next, we exploit the data further to see which kind of expenditures increased among poorer households. We look at non-durables, durables, and services. Based on the literature on transitory income shocks, one might expect to see large increases in durables and discretionary services. However, given how poor households are in the lowest quintile, it is less obvious that should be the case. Tables 9 and 10 use the specification from column (5) of Table 8 to examine the components of household expenditures. Table 9 looks at some major non-durable good and service categories and finds similar relative increases as overall expenditures. Relative to the top quintile, lower quintile households show increases during and after demonetization in expenditures on food, clothing, cosmetics, rent, power, and transportation.[52] The largest effects here are in clothing and power. The latter is consistent with our district results on night lights. Some further insights can be gained by looking at summary statistics for these categories by quintiles pre and post demonetization (and also in relation to total expenditures in Table 7). These statistics are provided in appendix Tables B.1 and B.2. When we look at the specific categories discussed so far, it is easy to infer that the percentage increases for quintile 1 are uniformly greater than that of 5th quintile. Clothing in particular, shows a raw 50% jump for the poorest group. In some

[52]The categories in both tables reflect the survey questionnaire. Clothing includes footwear, cosmetics include toiletries, rent includes home rental and other property charges, power includes both home energy bills, as well as gas and diesel, transportation includes fees and fares.

cases, the richest quintile shows a slight decline, in keeping with the total expenditures for this group.[53]

Table 10 repeats the estimation strategy of Table 9 for additional categories - appliances, intoxicants, recreation (goods and services), restaurants, and loan payments (EMI's) on cars and durable goods. To some degree, the categories in this table reflect more discretionary purchases.[54] As seen there are sizable and statistically significant relative increase among the bottom 4 quintiles in expenditures on appliances, intoxicants, recreation, and restaurants. We do not see a relative increase in the financing of vehicles or durables in columns (5) and (6), which respectively consider spending on equal monthly installments (EMI) for each. Referring to the summary statistics in appendix Tables B.3 and B.4, we can see that in general all these categories have really small values relative to total expenditures in their respective quintiles. The small magnitudes notwithstanding, the actual raw percentage increase for the lowest quintile is quite sizeable for appliances, recreation, and also EMI's.[55] To conclude the analysis, the relative increase in expenditures for the lowest quintile is also reflected in statistically significant increases in all major categories of expenses, with varying degrees of magnitude.

Income If the redistribution hypothesis is correct for the medium term, then we should also observe this in household income. It would be unusual to observe eighteen months of rising relative expenditures, without increases in reported income. Figure 10 plots the mean of the natural log of total household income by quintiles while the summary statistics are presented in Table 7.[56] As with expenditures, there are increases in incomes during demonetization for the lowest quintile, and decreases for the highest quintile. All households show increases post demonetization. Table 11 formally tests the relative effect of quintiles (omitting the top quintile) on the natural log of income both during and after demonetization; columns mirror those in Table 8. We see very similar effects as with expenditures: relative increases of the lower 4 quintiles during demonetization–due to the larger relative decline of the top quintile in Figure 10, followed by statistically significant relative increases in the natural log of income in the 16 months after demonetization. Again, this effect is largest for those in the bottom quintile, statistically so for the post-demonetization period.

The month-by-month effects of column (5) of Table 11 are plotted (relative to October

[53] It is worth nothing that rent constitutes a very small portion of expenses even for the poorest households, suggesting ownership is the norm.

[54] Appliances generally include small and large kitchen appliances ranging from toaster ovens to refrigerators, as well as big ticket electronics like TV's. Recreation includes both goods and services, e.g. music cd's, computer peripherals, concert tickets.

[55] Another unusual aspect of the survey is the fairly high values reported for intoxicants relative to other categories across all quintiles.

[56] We continue to use the same expenditure based quintiles as earlier.

2016) in Figure 11. As with expenditures, there is a slight increase from lower quintiles relative to the top quintile in the September of 2016, otherwise, there are no months that show significantly higher relative expenditures in the pre-period. In the post-demonetization period, however, there is a consistent positive effect on the natural log of income.

The Consumer Pyramids survey also provides information on different sources of income. Here we look at the some of the major sources that are of interest - wage income, business income, government transfers, and private transfers.[57] When looking at the components of household income in Table 12, we again see support for redistribution. Households in the lower quintiles show relative and statistically significant increases both during and after demonetization for wages and private transfers, but we find no significant effects of quintile differences in business income (negative following demonetization) and government transfers. For many households, particularly those in agriculture, an important component is non-market income. The survey imputes a value for this. In column (5) we confirm that imputed values are not driving our income results. Wage income and private transfers confirm our hypothesis. The negative sign for business income is a little more puzzling. The summary statistics by income source presented in the appendix Tables B.5 and B.6 provide some further insight. Business income went up for all groups, and the percentage increase is actually greatest for the poorest quintile. However, the post-demonetization value for the richest groups is an order of magnitude larger. One possibility is that, demonetization indeed forced greater formalization, or alternatively, did have some effect on the rich declaring more of their income.

Taken together the relative increase in expenditures and incomes from poorer households is suggestive of redistribution that possibly increased aggregate output following demonetization. The relative expenditure increase appears across a variety of goods and services. The relative increases to income is driven by wages and private transfers, two potential channels associated with redistribution.

5 Conclusion

If there is one thing that is clear from our analysis, it is that the medium term effects of India's demonetization experiment was quite different, if not the polar opposite of the short run disruption. These expansionary effects of demonetization are even seen in the raw aggregate statistics, from night time lights (Figure 1) to household income and expenditures (Figure 4).

Using night light data, we find that initial chaos from the shock led to temporary relative

[57] Other sources not included here because of their relatively small values, are dividend and interest, rental income, gambling income, sale of assets, and pension.

reductions in regional economic activity. Throughout 2017 and early 2018, the initial declines were overcome and surpassed by increases in economic activity, as captured by nighttime lights. To identify spatial variation in the effects of demonetization, we initially focus on deposit growth between the quarters preceding and following demonetization. While capturing the regular deposit of notes, this is also conducive to picking up the spatial aspects of potential redistribution. Ideally, one would like to have even more granular account data. Nevertheless, deposit growth turns out to be quite informative on its own. Given the nature of demonetization—an unanticipated macroeconomic shock, our primary analysis examines differential trends in nightlights following demonetization stemming from differences in demonetization-centered deposit growth. Our primary evidence for the effects of demonetization are given by Figure 5 and Table 2, where we show that compared to the months preceding demonetization, there is a clear decline during the enactment of demonetization in November and December of 2016, but after this initial disturbance, there is a clear positive impact. The positive effect is robust to many specifications and controls.

Next, we present evidence suggesting that demonetization had redistributive outcomes. We present evidence using both regional (district) and household level data. The regional outcomes are best captured in Table 5, which strong associations between demonetization-centered deposit growth and characteristics of districts that were relatively poorer. Figure 7 confirms these use of the alternative measures of district characteristics by showing each has the same pattern as our base analysis of Figure 5. We corroborate our regional analysis by looking at a panel of household incomes and expenditures. Here too, we show that the households in the poorest expenditure quintiles experienced larger increases post demonetization (in fact, also during demonetization.). We find that this is true for a variety of expenditure cateogries as well, and the increases in income are driven mainly by increases in wages and private transfers.

While our evidence for redistribution is strong, we admittedly do not pinpoint a specific channel. We discuss mechanisms such as asymmetric changes in expectations, money laundering, and also formalization and credit, much more research needs to be done to evaluate their relative importance, and perhaps even unearth ones not mentioned here. What is clear though, the increase can hardly be attributed to the avowed gains from demonetization. While the government might have counted on large scale wealth shocks (and our research seems to indicates there is reason to believe some costs were imposed), increased tax base, and reduction in counterfeit currency, the evidence indicates that the effects of these, at least at the time of writing were minimal.

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Tables and Figures

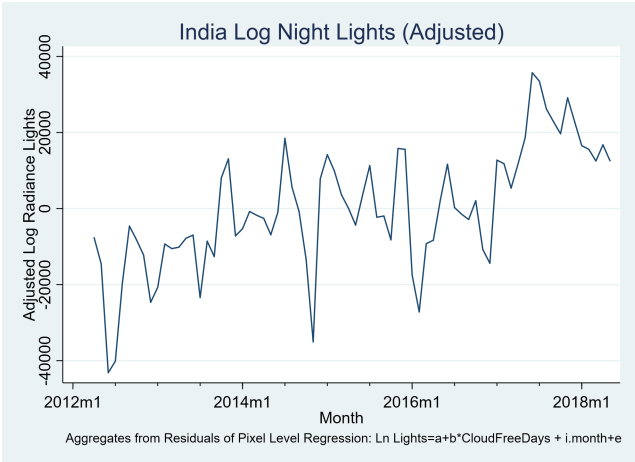


Figure 1: Nighttime Lights (India, demeaned)

Summary & Notes: This figure plots nighttime lights–demeaned by month and cloud free days–by month. As seen, this relatively unaltered data shows a clear increase in nighttime lights following demonetization in November of 2016.

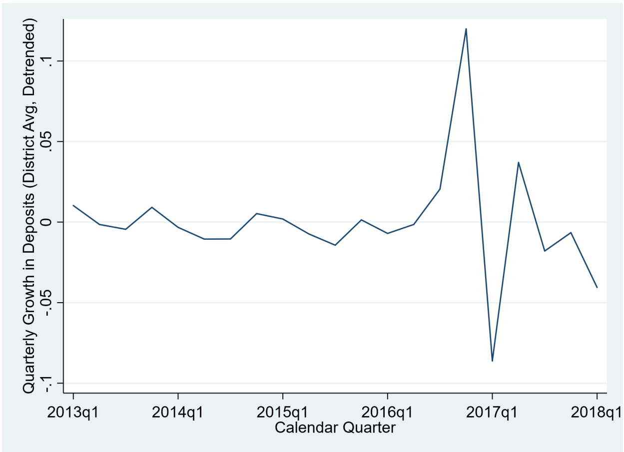


Figure 2: Quarterly Growth in Deposits

Summary & Notes: This figure plots the mean of district level quarterly growth rate of deposits relative to the quarterly mean (2011-2015 average of corresponding quarters). As shown, there is a large relative increase in deposits centered around demonetization.

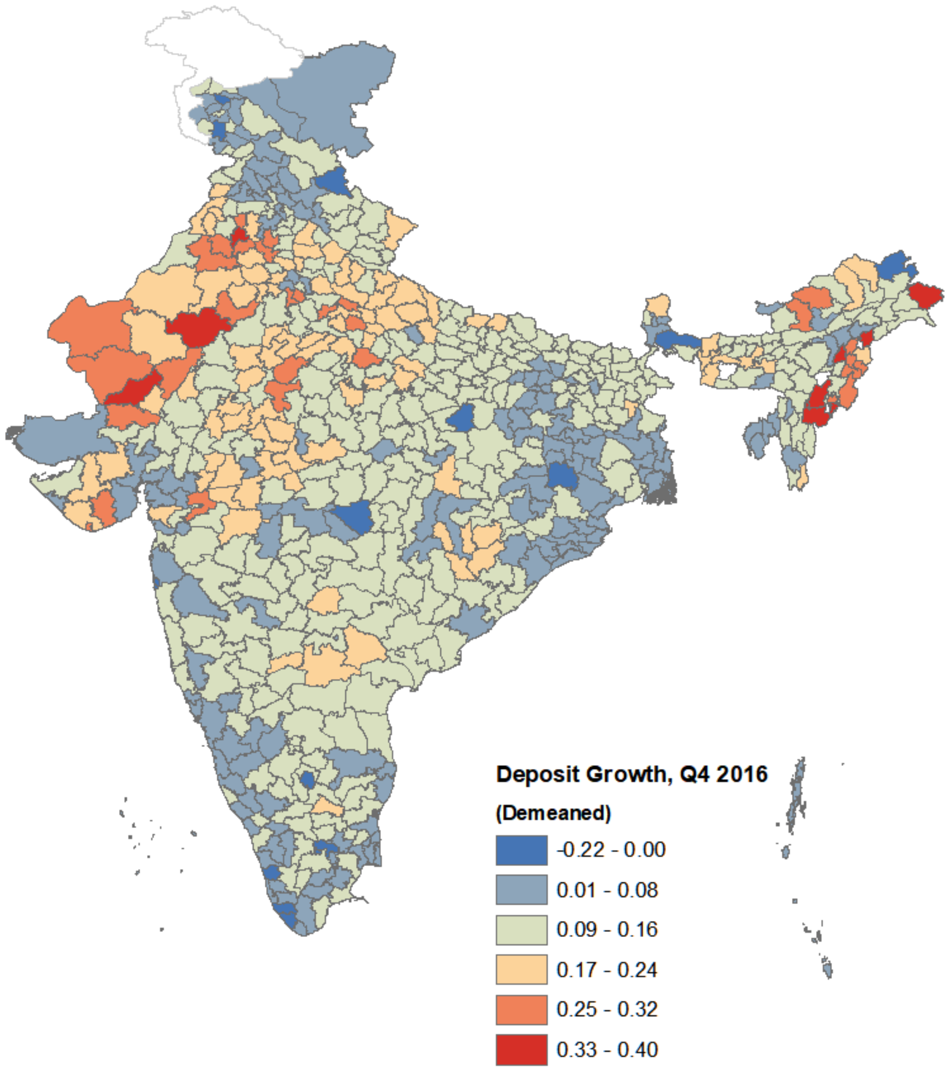


Figure 3: 4th Quarter Deposit Growth by District

Summary & Notes: This map shows the district level quarterly growth rate of deposits between the 3rd and 4th Quarter of 2016 relative to the quarterly mean (2011-2015 average growth for the corresponding district and quarter). Districts are based on the 2011 census.

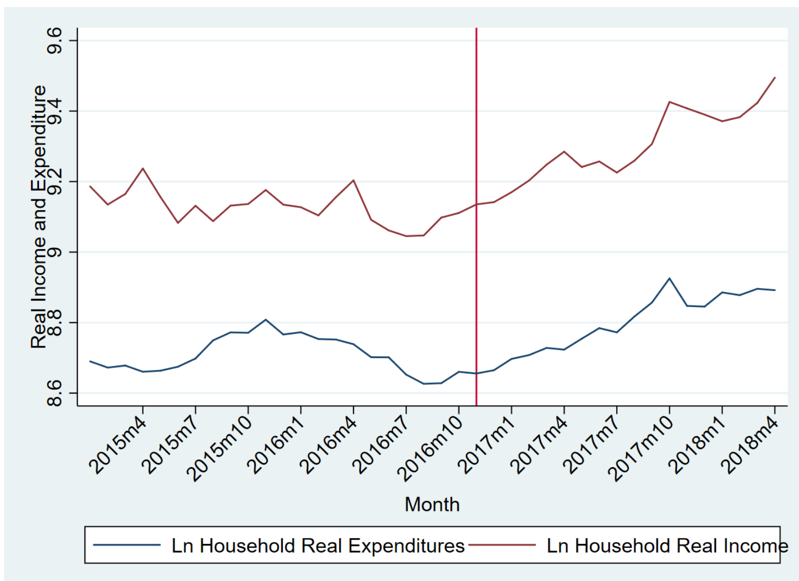


Figure 4: Real Household Income and Expenditures (Consumer Pyramids)

Summary & Notes: The figure shows household expenditures and incomes from the Consumer Pyramid survey. The values are deflated using the CPI (base 2012=100). Survey weights were used to arrive at the mean values depicted in the figure.

Table 1: District Summary Statistics

Variable	Obs.	Mean	Std Deviation	Min	Max
ln Nighttime Lights	25,625	9.426	1.060	0	12.334
Pre-Demonetization	13,750	9.261	1.098	0	12.334
During-Demonetization	1,250	9.239	1.189	4.380	12.257
Post-Demonetization	10,625	9.660	0.944	0	12.327
Time-Invariant District Measures					
Deposit Growth, 2016q3-2016q4	625	0.139	0.075	-0.246	0.583
Poverty Head Count Ratio, 2014-15	625	0.285	0.179	0.001	0.765
Literacy Rate, 2011	625	0.622	0.104	0.288	0.887
ln Annual Nighttime Lights (per km^2), 2015	625	0.645	1.396	-6.492	5.727
Share of Emp. in Small Firms, 2013-14	625	0.819	0.118	0.227	0.983
ln Accounts per Capita, 2014	625	-0.201	0.48	-2.161	1.439
Share of rural population, 2011	625	0.748	0.191	0	1
Time-Invariant District Controls					
ln Population, 2011	625	14.059	1.063	8.988	16.219
Land Area	625	5020.512	4909.628	9.067	68,466.88
Land Suitability					
Mean	625	0.543	0.215	0	0.927
Std. Dev.	625	0.043	0.036	0	0.236
Historic Rainfall					
Mean	625	1292.859	742.500	102.155	5325.912
Std. Dev.	625	145.176	198.060	8.415	1716.64
Malaria Suitability					
Mean	625	0.119	0.486	0	8.188
Std. Dev.	625	0.012	0.089	0	1.177
Temperature					
Mean	625	240.876	47.839	-54.266	289.971
Std. Dev.	625	9.561	14.843	0.144	87.36
Ruggedness					
Mean	625	102,469	167,631	0	862,243
Std. Dev.	625	73,471	79,359	0	373,594
Ecosystem Ind.					
Trop. Moist Broadleaf	625	0.434	0.496	0	1
Trop. Dry Broadleaf	625	0.270	0.445	0	1
Trop. Coniferous	625	0.030	0.171	0	1
Temp. Broadleaf	625	0.056	0.230	0	1
Temp. Coniferous	625	0.010	0.098	0	1
Trop. Grassland	625	0.008	0.0891	0	1
Flooded Grassland	625	0.002	0.04	0	1
Montane Grassland	625	0.029	0.167	0	1
Desert	625	0.157	0.364	0	1
Mangroves	625	0.005	0.069	0	1
Time-Variant (Monthly) District Controls					
Cloud Free Days	25,625	9.974	4.888	0	21.653
Contemporary Rainfall	25,625	92.775	154.217	0	2,603.8

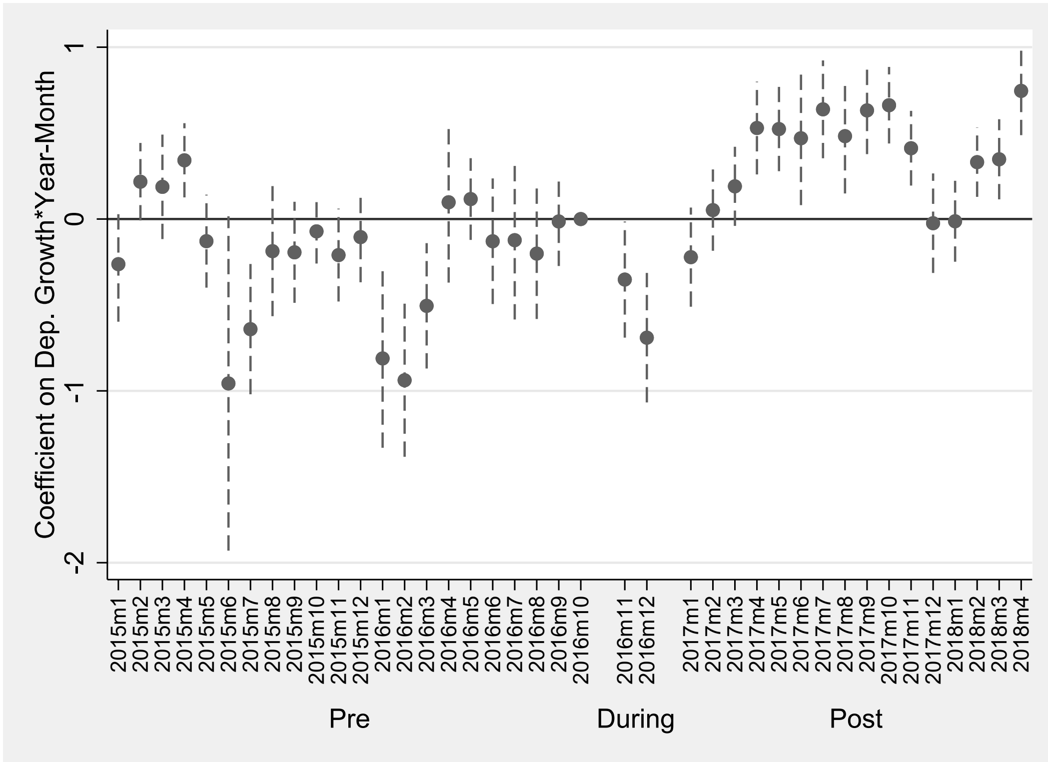


Figure 5: Event Figure- Growth of Deposits 2016q3-2016q4

Summary & Notes: This figure plots the relationship between our primary measure of demonetization intensity and nighttime lights by month, omitting the period prior to demonetization (Oct. 2016). The specification follows that of col. (5) of Table 2. No clear relationship exists prior to demonetization; during demonetization a negative coefficient is estimated; and after demonetization a general positive relationships is seen.

Table 2: Base estimation
The change in nighttime lights from demonetization

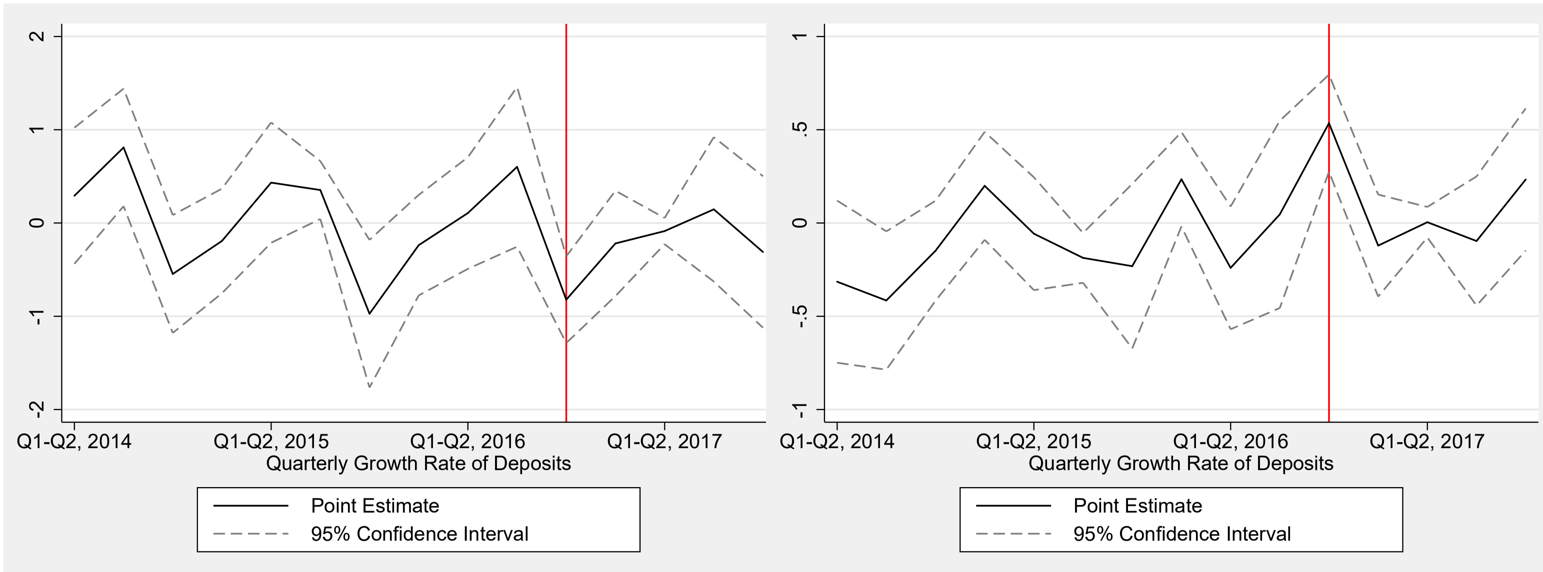
	(1)	(2)	(3)	(4)	(5)
Dependent variable: ln of monthly night time lights, Jan. 2015 - April 2018					
$I_{During} \times$ Deposit Growth, 2016q3-2016q4	-0.689***	-0.690***	-0.366**	-0.744***	-0.316*
	(0.221)	(0.222)	(0.159)	(0.213)	(0.168)
	[0.221]	[0.222]	[0.155]	[0.208]	[0.163]
	{0.223}	{0.227}	{0.167}	{0.213}	{0.174}
$I_{Post} \times$ Deposit Growth, 2016q3-2016q4	0.550***	0.593***	0.431***	0.762***	0.565***
	(0.124)	(0.126)	(0.111)	(0.110)	(0.114)
	[0.089]	[0.090]	[0.080]	[0.079]	[0.081]
	{0.092}	{0.093}	{0.084}	{0.082}	{0.086}
Controls:					
ln Cloud Free Days		Y	Y	Y	Y
ln Population 2011 $\times$ During & Post			Y		Y
Geoclimatic Controls $\times$ During & Post				Y	Y
ln Monthly Rainfall				Y	Y
District FE	Y	Y	Y	Y	Y
State-year-month FE	Y	Y	Y	Y	Y
Districts	625	625	625	625	625
Months	40	40	40	40	40
Observations	25000	25000	25000	25000	25000
r2	0.945	0.948	0.950	0.950	0.951

Summary & Notes: This table represents our baseline estimation. We use the quarterly growth in deposits from demonetization to measure a district's intensity of exposure to demonetization. We then look at the relative difference on nighttime lights for the initial implementation period–i.e., $I_{During} = 1$ for November and December 2016–and at the longer term effects of demonetization–i.e., $I_{Post} = 1$ for January 2017 till April 2018. Geoclimatic controls include the district-level mean and standard deviation of agricultural suitability, precipitation, temperature, malaria suitability; and mean of ruggedness, area, coastal land, and indicators for each biome. Time invariant controls are interacted with I_{During} and I_{Post}. Standard errors are clustered by district in parentheses–"( )"–and by spatially adjusted district for 30km in brackets–"[ ]"–and 200km in braces–"{ }". Statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

Table 3: Placebo test: Alternative treatment date

Dependent variable: ln of monthly night time lights, Jan. 2014 - Oct. 2016	(1)	(2)	(3)	(4)	(5)
$I_{During,t-12} \times$ Deposit Growth, 2016q3-2016q4	0.036	0.040	0.114	0.030	0.142*
	(0.098)	(0.098)	(0.111)	(0.087)	(0.086)
$I_{Post,t-12} \times$ Deposit Growth, 2016q3-2016q4	-0.052	-0.054	-0.006	-0.120	-0.093
	(0.085)	(0.083)	(0.090)	(0.084)	(0.091)
Controls:					
ln Cloud Free Days		Y	Y	Y	Y
ln Population 2011 $\times$ During & Post			Y		Y
Geoclimatic Controls $\times$ During & Post				Y	Y
ln Monthly Rainfall				Y	Y
District FE	Y	Y	Y	Y	Y
State-year-month FE	Y	Y	Y	Y	Y
Districts	625	625	625	625	625
Months	34	34	34	34	34
Observations	21250	21250	21250	21250	21250
R Sqr.	0.942	0.945	0.946	0.946	0.946

Summary & Notes: This table moves the treatment date back by a year to November of 2015. Compared to the coefficients of Table 2, the magnitudes are generally lessened and the opposite sign, and no statistically significant coefficients are estimated. This table confirms November 2016 as the true treatment date. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.



(a) $I_{During} \times Qtr.Growth$ **(b)** $I_{Post} \times Qtr.Growth$

Figure 6: Effects from Quarterly Growth in Deposits for All Quarters

Summary & Notes: This figure plots coefficients from the regression specification of column (5) of Table 2 , replacing the change in deposits centered around demonetization with the specified quarterly change. Sub-figure (a) plots the effect of the specified quarterly growth of deposits on nighttime lights in the immediate months of demonetization (Nov. and Dec. 2016), and sub-figure (b) plots coefficients from the same regression for months in the post period. The red reference line marks 2016 Q3-Q4 growth in deposits. As seen the largest estimated effect on nighttime lights is seen for the change in deposits around demonetization. This supports our use of the 2016 Q3-Q4 growth in deposits as a measure of the intensity of demonetization.

Table 4: Controlling for Pretrends

	(1)	(2)	(3)	(4)
Dependent variable: ln of monthly night time lights, Jan. 2015 - April 2018				
During Demonetization Indicator ×				
Deposit Growth, 2016q3-2016q4	-0.3220*	-0.1972	-0.2120	-0.1680
	(0.1677)	(0.1878)	(0.1798)	(0.1732)
Mean Deposit Growth, 2014q1-2016q3	-0.3800		-0.9848	-0.8527
	(0.8000)		(0.7845)	(0.7558)
Mean Light Growth, Jan. 2014-Oct. 2016		-12.8676***	-12.9773***	-12.6388***
		(1.9865)	(1.9704)	(1.9532)
Deposit Growth, 2016q2-2016q3				0.4821
				(0.2986)
Deposit Growth, 2015q3-2015q4				-0.5854*
				(0.3368)
Post Demonetization Indicator ×				
Deposit Growth, 2016q3-2016q4	0.5545***	0.4742***	0.4710***	0.5103***
	(0.1116)	(0.0858)	(0.0864)	(0.0869)
Mean Deposit Growth, 2014q1-2016q3	-0.6718		-0.2141	-0.2220
	(0.4753)		(0.3791)	(0.3695)
Mean Light Growth, Jan. 2014-Oct. 2016		9.8248***	9.8009***	9.9082***
		(0.7387)	(0.7410)	(0.7310)
Deposit Growth, 2016q2-2016q3				-0.0602
				(0.1507)
Deposit Growth, 2015q3-2015q4				-0.4127**
				(0.1726)
Controls:				
ln Cloud Free Days	Y	Y	Y	Y
ln Population 2011 × During & Post	Y	Y	Y	Y
Geoclimatic Controls × During & Post	Y	Y	Y	Y
ln Monthly Rainfall	Y	Y	Y	Y
District FE	Y	Y	Y	Y
State-year-month FE	Y	Y	Y	Y
Districts	625	625	625	625
Months	40	40	40	40
Observations	25000	25000	25000	25000
r2	0.9511	0.9525	0.9526	0.9526

Summary & Notes: This table controls for the effect from differing quarterly changes in deposits to show that our base measure–i.e., the change in deposits centered around demonetization–is what is driving the findings of Table 2. We also explicitly control for the average growth rate of nighttime lights during the pre-period. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

Table 5: District Characteristics and Deposit Growth from Demonetization

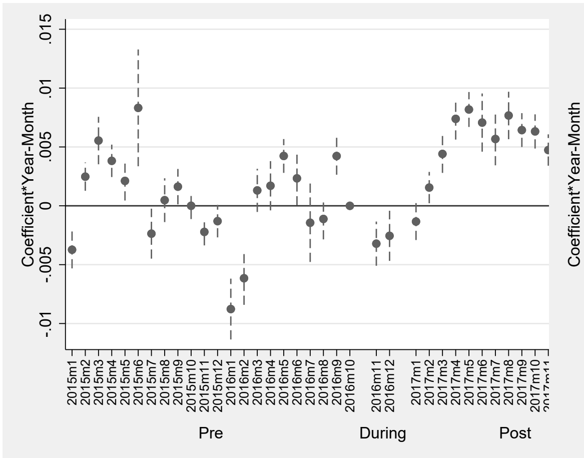
	Dependent variable: Deposit Growth, 2016q3-2016q4					
	(1)	(2)	(3)	(4)	(5)	(6)
Std. Poverty HCR (2014-15)	0.023^{***}					
	(0.005)					
Std. Literacy Rate (2011)		-0.032^{***}				
		(0.005)				
Std. Pre-period Lights (per km^2, 2015)			-0.032^{***}			
			(0.006)			
Std. Small Employment Share (2013-14)				0.016^{***}		
				(0.003)		
Std. Accounts per Capita (2014)					-0.046^{***}	
					(0.004)	
Std. Rural Share (2011)						0.027^{***}
						(0.004)
District Controls:						
ln Population 2011	Y	Y	Y	Y	Y	Y
Geoclimatic Controls	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Observations	625	625	625	625	625	625
r2	0.518	0.565	0.532	0.517	0.625	0.560

Summary & Notes: This table examines cross-district correlates with deposit growth from demonetization. A number of proxies show poorer districts had larger increases in deposit growth from demonetization. Geoclimatic controls include the district-level mean and standard deviation of agricultural suitability, precipitation, temperature, malaria suitability; and mean of ruggedness, area, coastal land, and indicators for each biome. Standard errors are clustered by state, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

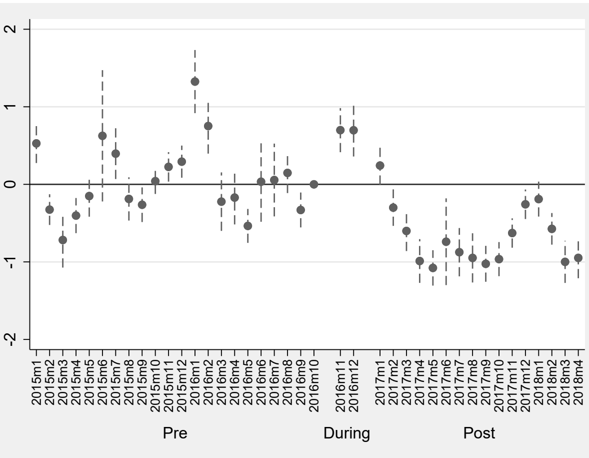
Table 6: District Characteristics and Deposit Growth prior to Demonetization

	Dependent variable: Deposit Growth, 2014q1-2016q3					
	(1)	(2)	(3)	(4)	(5)	(6)
Std. Poverty HCR (2014-15)	-0.001					
	(0.001)					
Std. Literacy Rate (2011)		0.001				
		(0.001)				
Std. Pre-period Lights (per km^2, 2015)			-0.002			
			(0.001)			
Std. Small Employment Share (2013-14)				-0.000		
				(0.001)		
Std. Accounts per Capita (2014)					-0.001	
					(0.001)	
Std. Rural Share (2011)						0.001
						(0.001)
District Controls:						
ln Population 2011	Y	Y	Y	Y	Y	Y
Geoclimatic Controls	Y	Y	Y	Y	Y	Y
State FE	Y	Y	Y	Y	Y	Y
Observations	625	625	625	625	625	625
r2	0.199	0.199	0.204	0.199	0.210	0.200

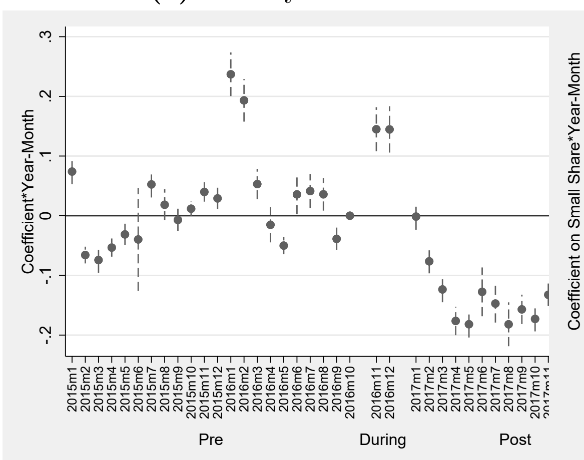
Summary & Notes: This table examines the relationship between the poverty proxies from Table 5 and mean deposit growth prior to demonetization. As shown, these measures have no statistical association with the average district level growth in deposits, suggesting that poorer districts did indeed receive a relatively larger amount of deposits from demonetization. Geoclimatic controls include the district-level mean and standard deviation of agricultural suitability, precipitation, temperature, malaria suitability; and mean of ruggedness, area, coastal land, and indicators for each biome. Standard errors are clustered by state, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.



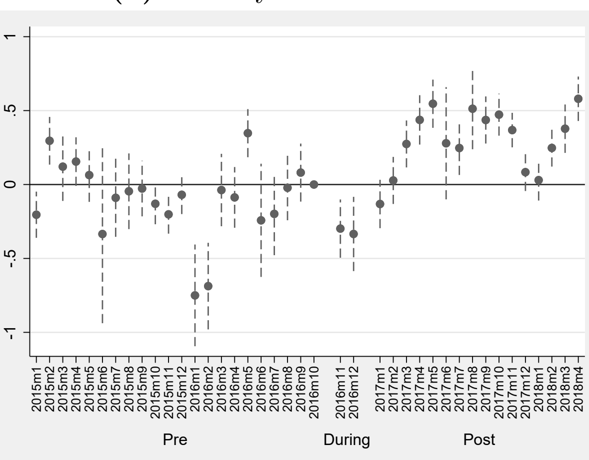
(a) Poverty HCR



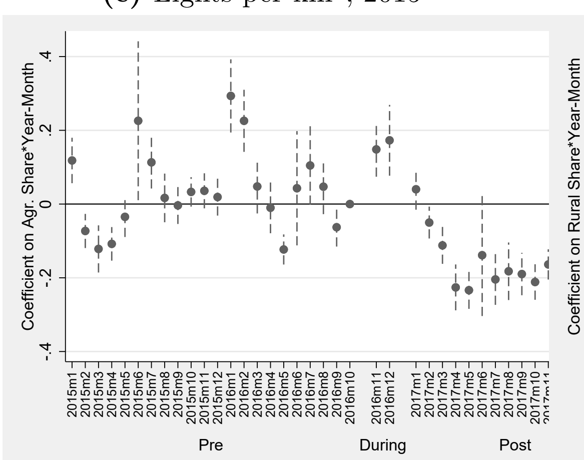
(b) Literacy Rate



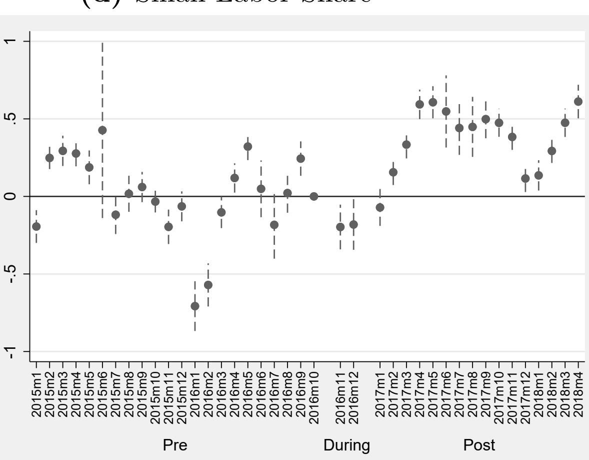
(c) Lights per km^2, 2015



(d) Small Labor Share



(e) ln Acct. per Capita, 2014



(f) Rural Pop. Share

Figure 7: Monthly Effect of District Characteristics on Nighttime Lights

Summary & Notes: This figure mirrors estimates from Fig. 5, replacing the monthly effect of Q3-Q4 deposit growth on the natural log of nighttime lights with the district-level correlates from Table 5. Sub-figure (a) considers the poverty headcount ratio; (b) the literacy rate from 2011; (c) annual lights from 2015; (c) the fraction of workers in small firms (less than 10 employees); (d) the natural log of accounts per capita in 2014; and (e) the rural population share from 2011.

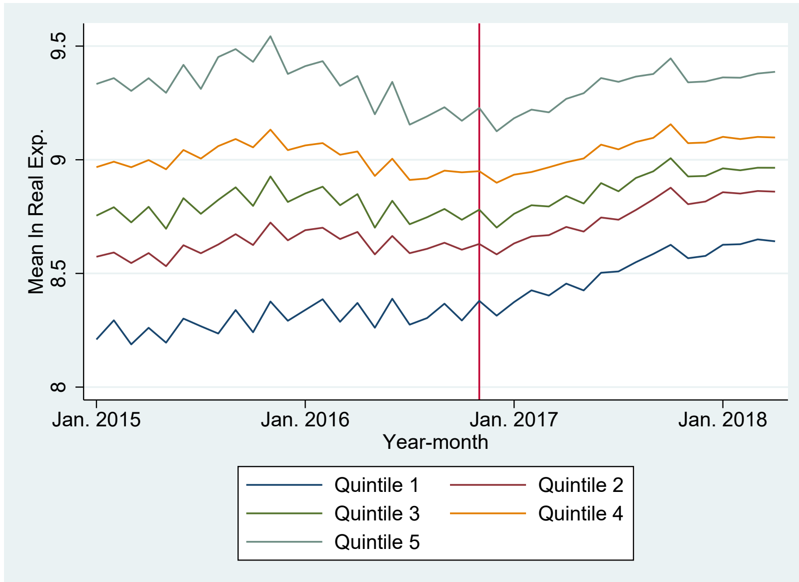


Figure 8: Mean ln Expenditures by Quintile

Summary & Notes: This figure plots mean natural log of real expenditures by initial (c.2015) quintiles of real expenditures. The vertical line marks the demonetization quarter (November 2016).

Table 7: Expenditure Summary Statistics

	All Periods Jan. 2015 - Apr. 2018	Pre Jan. 2015 - Oct. 2016	During Nov. 2016 - Dec. 2016	Post Jan. 2017 - Apr. 2018
Monthly Real Expenditures (in 100s of ₹)	80.57	78.02	74.00	85.17
	(56.25)	(53.73)	(48.16)	(60.36)
By initial expenditure quintiles:				
Quintile 1	49.30	44.48	47.54	56.59
	(32.77)	(19.85)	(22.95)	(45.32)
Quintile 2	63.96	59.78	60.46	70.53
	(31.35)	(22.93)	(30.62)	(39.84)
Quintile 3	74.74	71.67	69.66	79.90
	(34.92)	(27.56)	(33.04)	(43.20)
Quintile 4	89.86	87.78	83.13	93.78
	(43.32)	(34.47)	(40.68)	(53.68)
Quintile 5	130.29	132.32	114.14	129.46
	(87.15)	(89.08)	(73.14)	(85.77)
Monthly Real Income (in 100s of ₹)	133.69	124.83	125.51	147.70
	(133.26)	(121.35)	(121.85)	(149.17)
By initial expenditure quintiles:				
Quintile 1	73.83	65.20	72.88	86.57
	(59.10)	(49.07)	(52.86)	(70.02)
Quintile 2	96.96	88.61	92.61	109.76
	(75.90)	(65.77)	(67.01)	(88.08)
Quintile 3	114.77	106.58	107.84	127.67
	(93.59)	(83.03)	(82.65)	(107.13)
Quintile 4	149.12	140.42	139.53	163.06
	(126.50)	(112.48)	(111.34)	(145.06)
Quintile 5	245.87	235.58	227.20	263.21
	(201.50)	(182.01)	(192.32)	(226.72)

Table 8: Household Expenditure Effect by Pre-demonetization (Expenditure) Quintiles

	Dependent variable: ln Monthly Total Expenditures + 1; January 2015 - April 2018				
	(1)	(2)	(3)	(4)	(5)
$I_{During} \times$ Quintile:					
I pre-demon mth. expenditures quintile	0.201***	0.273***	0.292***	0.252***	0.298***
	(0.030)	(0.030)	(0.033)	(0.033)	(0.040)
II pre-demon mth. expenditures quintile	0.137***	0.198***	0.206***	0.183***	0.214***
	(0.023)	(0.022)	(0.022)	(0.023)	(0.027)
III pre-demon mth. expenditures quintile	0.104***	0.142***	0.152***	0.138***	0.160***
	(0.020)	(0.019)	(0.020)	(0.020)	(0.024)
IV pre-demon mth. expenditures quintile	0.074***	0.098***	0.106***	0.098***	0.110***
	(0.016)	(0.012)	(0.013)	(0.013)	(0.015)
$I_{Post} \times$ Quintile:					
I pre-demon mth. expenditures quintile	0.239***	0.348***	0.385***	0.327***	0.406***
	(0.041)	(0.039)	(0.042)	(0.043)	(0.053)
II pre-demon mth. expenditures quintile	0.155***	0.253***	0.281***	0.249***	0.302***
	(0.028)	(0.030)	(0.027)	(0.027)	(0.034)
III pre-demon mth. expenditures quintile	0.113***	0.196***	0.223***	0.202***	0.240***
	(0.023)	(0.030)	(0.027)	(0.027)	(0.032)
IV pre-demon mth. expenditures quintile	0.052***	0.126***	0.145***	0.135***	0.156***
	(0.020)	(0.022)	(0.019)	(0.019)	(0.022)
Controls:					
Household FE	Y	Y	Y	Y	Y
Year-month FE	Y				
Year-month by State FE		Y			
Year-month by District FE			Y	Y	Y
HH Size and Earning Member FE				Y	Y
Months from Interview FE				Y	Y
Household characteristics ($\times$ I_{During}&I_{Post})					Y
Households	144,117	144,117	144,117	144,117	144,117
Months (unbalanced)†	40	40	40	40	40
Observations	4,804,111	4,804,111	4,804,111	4,804,111	4,804,111
r2	0.403	0.505	0.563	0.573	0.574

Summary & Notes: This table tests whether poorer households–measured by quintiles of mean monthly 2015 real expenditures–had larger increases in expenditures during and following demonetization. Indeed, lower quintiles had larger relative increases in expenditures both during and post demonetization. As noted in Fig. 8, the positive during demonetization coefficient likely represents a smaller relative decline, while the post demonetization effect represents a relative increase. Household characteristics include a rural indicator, mean years of schooling of members 25 and older, mean age, the number of members under 16 years of age, and separate indicators for religion and caste. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.
† The mean by months of households in the panel is 34.79.

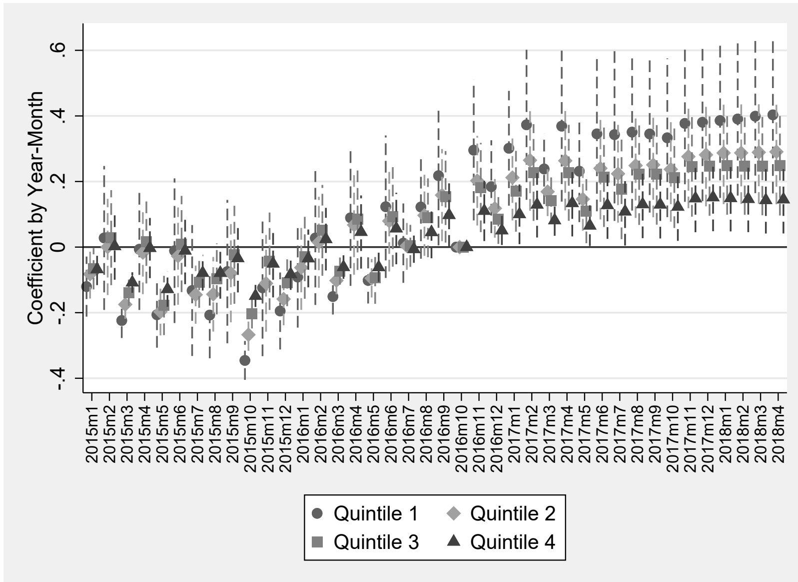


Figure 9: Expenditure Effects for Household Quintiles by Month

Summary & Notes: This figure plots the monthly effect on household expenditures for the lower 4 quintiles relative to the top quintile compared to October 2016, the month prior to demonetization. A slight negative to insignificant difference is seen between most of the lower 4 quintiles and the top quintile prior to demonetization, but a clear and consistent positive effect, suggesting relative increases among the lower quintiles, is seen after demonetization. The estimation specification follows that of column (5) of Table 8.

Table 9: Expenditure Components by Quintiles (I)

Dependent variable: ln (Monthly Expenditures + 1) from:	Food	Clothes	Cosmetics	Rent	Power	Transportation
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{During} \times$ Quintile:						
I pre-demon mth. expenditures quintile	0.173***	0.819***	0.230***	0.213***	0.356***	0.219***
	(0.033)	(0.059)	(0.030)	(0.057)	(0.031)	(0.053)
II pre-demon mth. expenditures quintile	0.114***	0.617***	0.161***	0.146***	0.256***	0.136***
	(0.023)	(0.049)	(0.022)	(0.053)	(0.025)	(0.042)
III pre-demon mth. expenditures quintile	0.083***	0.509***	0.114***	0.117**	0.197***	0.084**
	(0.020)	(0.043)	(0.019)	(0.054)	(0.022)	(0.035)
IV pre-demon mth. expenditures quintile	0.051***	0.348***	0.081***	0.134***	0.123***	0.037
	(0.013)	(0.035)	(0.012)	(0.046)	(0.016)	(0.026)
$I_{Post} \times$ Quintile:						
I pre-demon mth. expenditures quintile	0.262***	0.864***	0.304***	0.349***	0.460***	0.296***
	(0.046)	(0.058)	(0.040)	(0.055)	(0.039)	(0.055)
II pre-demon mth. expenditures quintile	0.186***	0.659***	0.222***	0.262***	0.351***	0.205***
	(0.031)	(0.042)	(0.026)	(0.049)	(0.030)	(0.041)
III pre-demon mth. expenditures quintile	0.151***	0.507***	0.169***	0.210***	0.281***	0.154***
	(0.029)	(0.034)	(0.024)	(0.050)	(0.028)	(0.037)
IV pre-demon mth. expenditures quintile	0.092***	0.335***	0.110***	0.170***	0.180***	0.091***
	(0.020)	(0.027)	(0.017)	(0.045)	(0.022)	(0.029)
Controls and Weights:						
Household FE	Y	Y	Y	Y	Y	Y
Year-month by District FE	Y	Y	Y	Y	Y	Y
HH Size and Earning Member FE	Y	Y	Y	Y	Y	Y
Months from Interview FE	Y	Y	Y	Y	Y	Y
Household characteristics ($\times$ I_{During}&I_{Post})	Y	Y	Y	Y	Y	Y
Households	144,117	144,117	144,117	144,117	144,117	144,117
Months (unbalanced)	40	40	40	40	40	40
Observations	4,804,111	4,804,111	4,804,111	4,804,111	4,804,111	4,804,111
r2	0.575	0.427	0.587	0.663	0.485	0.472

Summary & Notes: This table replicates the specification of column (5) of Table 8, swapping overall monthly expenditures with notable components of expenditures. As with overall expenditures, poorer households generally had larger relative responses during and after demonetization. Household characteristics include a rural indicator, mean years of schooling of members 25 and older, mean age, the number of members under 14 years of age, and separate indicators for religion and caste.Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

† The mean by months of households in the panel is 34.79.

Table 10: Expenditure Components by Quintiles (II)

Dependent variable: ln (Monthly Expenditures + 1) from:	Appliances	Intoxicants	Recreation	Restaurants	Vehicle EMI	Durable EMI
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{During} \times$ Quintile:						
I pre-demon mth. expenditures quintile	0.274***	0.448***	0.343***	0.638***	0.023*	0.011*
	(0.053)	(0.058)	(0.051)	(0.063)	(0.014)	(0.006)
II pre-demon mth. expenditures quintile	0.232***	0.273***	0.253***	0.517***	0.016	0.015**
	(0.046)	(0.051)	(0.047)	(0.057)	(0.013)	(0.006)
III pre-demon mth. expenditures quintile	0.156***	0.227***	0.195***	0.376***	0.015	0.012**
	(0.036)	(0.047)	(0.041)	(0.053)	(0.013)	(0.006)
IV pre-demon mth. expenditures quintile	0.105***	0.175***	0.105***	0.304***	0.006	0.005
	(0.028)	(0.048)	(0.036)	(0.041)	(0.013)	(0.005)
$I_{Post} \times$ Quintile:						
I pre-demon mth. expenditures quintile	0.287***	0.514***	0.314***	0.745***	-0.024	-0.002
	(0.055)	(0.059)	(0.052)	(0.057)	(0.016)	(0.007)
II pre-demon mth. expenditures quintile	0.222***	0.355***	0.247***	0.589***	-0.011	0.006
	(0.044)	(0.052)	(0.043)	(0.053)	(0.016)	(0.006)
III pre-demon mth. expenditures quintile	0.158***	0.311***	0.209***	0.446***	-0.008	0.013**
	(0.035)	(0.051)	(0.038)	(0.048)	(0.016)	(0.006)
IV pre-demon mth. expenditures quintile	0.103***	0.231***	0.127***	0.328***	-0.009	0.009
	(0.029)	(0.045)	(0.034)	(0.038)	(0.018)	(0.006)
Controls:						
Household FE	Y	Y	Y	Y	Y	Y
Year-month by District FE	Y	Y	Y	Y	Y	Y
HH Size and Earning Member FE	Y	Y	Y	Y	Y	Y
Months from Interview FE	Y	Y	Y	Y	Y	Y
Household characteristics ($\times$ I_{During}&I_{Post})	Y	Y	Y	Y	Y	Y
Households	144,117	144,117	144,117	144,117	144,117	144,117
Months (unbalanced)	40	40	40	40	40	40
Observations	4,804,111	4,804,111	4,804,111	4,804,111	4,804,111	4,804,111
r2	0.375	0.537	0.404	0.523	0.290	0.213

Summary & Notes: This table replicates the specification of column (5) of Table 8, swapping overall monthly expenditures with notable components of expenditures. As with overall expenditures, poorer households generally had larger relative responses during and after demonetization. Household characteristics include a rural indicator, mean years of schooling of members 25 and older, mean age, the number of members under 14 years of age, and separate indicators for religion and caste.Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.
† The mean by months of households in the panel is 34.79.

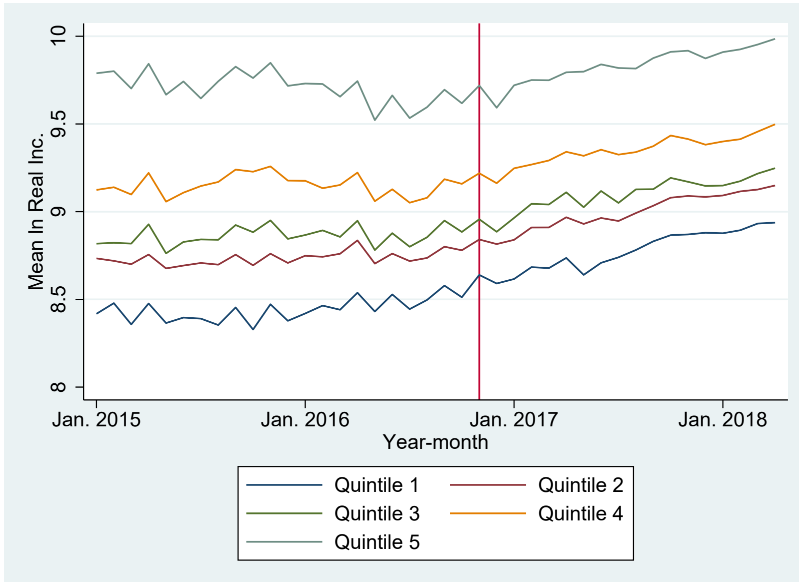


Figure 10: Mean ln Income by Quintile

Summary & Notes: This figure plots mean natural log of real incomes by initial (2015) quintiles of real expenditures. The vertical line marks the demonetization month (November 2016).

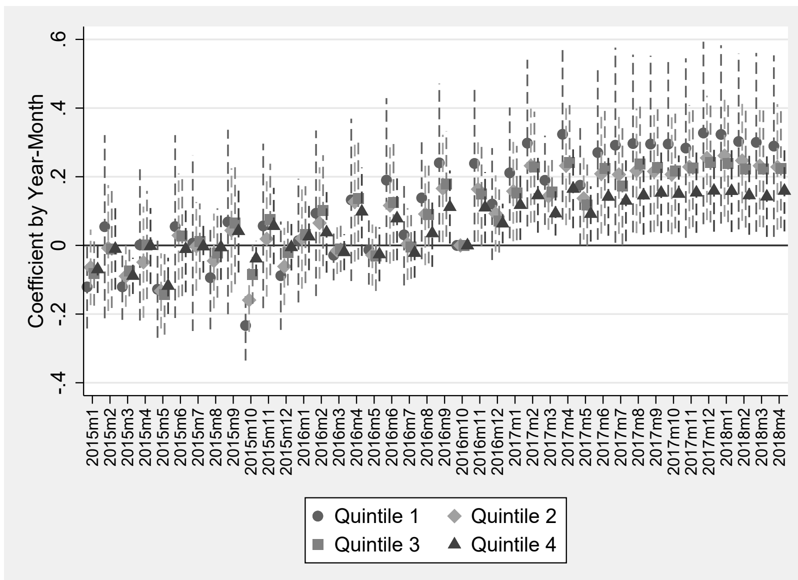


Figure 11: Income Effects for Household Quintiles by Month

Summary & Notes: This figure plots the monthly effect on household income for the lower 4 expenditure quintiles relative to the top quintile compared to October 2016, the month prior to demonetization. A slight negative to insignificant difference is seen between most of the lower 4 quintiles and the top quintile prior to demonetization, but a clear and consistent positive effect, suggesting relative increases among the lower quintiles, is seen after demonetization. The estimation specification follows that of column (5) of Table 8.

Table 11: Household Income Effect by Pre-demonetization (Expenditure) Quintiles

Dependent variable: ln Monthly Total Income + 1; January 2015 - April 2018	(1)	(2)	(3)	(4)	(5)
$I_{During}\times$ Quintile:					
I pre-demon mth. expenditures quintile	0.203***	0.255***	0.254***	0.164***	0.165***
	(0.033)	(0.033)	(0.033)	(0.034)	(0.040)
II pre-demon mth. expenditures quintile	0.132***	0.166***	0.177***	0.121***	0.125***
	(0.030)	(0.031)	(0.028)	(0.028)	(0.030)
III pre-demon mth. expenditures quintile	0.098***	0.115***	0.126***	0.089***	0.093***
	(0.031)	(0.032)	(0.027)	(0.027)	(0.028)
IV pre-demon mth. expenditures quintile	0.083***	0.092***	0.098***	0.080***	0.083***
	(0.022)	(0.022)	(0.018)	(0.017)	(0.018)
$I_{Post}\times$ Quintile:					
I pre-demon mth. expenditures quintile	0.185***	0.333***	0.354***	0.237***	0.264***
	(0.042)	(0.041)	(0.041)	(0.042)	(0.052)
II pre-demon mth. expenditures quintile	0.127***	0.246***	0.262***	0.184***	0.210***
	(0.030)	(0.036)	(0.031)	(0.031)	(0.037)
III pre-demon mth. expenditures quintile	0.111***	0.206***	0.227***	0.171***	0.191***
	(0.027)	(0.037)	(0.031)	(0.031)	(0.036)
IV pre-demon mth. expenditures quintile	0.069***	0.144***	0.149***	0.123***	0.137***
	(0.023)	(0.027)	(0.022)	(0.022)	(0.024)
Controls:					
Household FE	Y	Y	Y	Y	Y
Year-month FE	Y				
Year-month by State FE		Y			
Year-month by District FE			Y	Y	Y
HH Size and Earning Member FE				Y	Y
Months from Interview FE				Y	Y
Household characteristics ($\times$ I_{During}&I_{Post})					Y
Households	144,117	144,117	144,117	144,117	144,117
Months (unbalanced)	40	40	40	40	40
Observations	4,804,111	4,804,111	4,804,111	4,804,111	4,804,111
r2	0.338	0.367	0.422	0.446	0.447

Summary & Notes: This table tests whether poorer households–measured by quintiles of mean monthly 2015 real expenditures–had larger increases in income during and following demonetization. Indeed, lower quintiles had larger relative increases in income both during and post demonetization. As noted in Fig. 10, the positive during demonetization coefficient represents a smaller relative decline, while the post demonetization effect represents a relative increase. Household characteristics include a rural indicator, mean years of schooling of members 25 and older, mean age, the number of members under 14 years of age, and separate indicators for religion and caste. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.
† The mean by months of households in the panel is 34.79.

Table 12: Components of Income by Quintiles

Dependent variable: ln (Monthly HH Income + 1) from:	Wages	Business	Govt. Trans.	Priv. Trans.	Imputed
	(1)	(2)	(3)	(4)	(5)
$I_{During} \times$ Quintile:					
I pre-demon mth. expenditures quintile	0.157***	-0.006	-0.046	0.100***	-0.025
	(0.042)	(0.023)	(0.031)	(0.019)	(0.028)
II pre-demon mth. expenditures quintile	0.172***	-0.000	-0.022	0.050***	0.020
	(0.035)	(0.023)	(0.027)	(0.015)	(0.025)
III pre-demon mth. expenditures quintile	0.148***	0.011	0.011	0.029**	0.037*
	(0.033)	(0.018)	(0.021)	(0.012)	(0.021)
IV pre-demon mth. expenditures quintile	0.125***	0.024	0.054***	0.021**	0.039**
	(0.025)	(0.015)	(0.016)	(0.010)	(0.018)
$I_{Post} \times$ Quintile:					
I pre-demon mth. expenditures quintile	0.424***	-0.206***	-0.097**	0.108***	-0.029
	(0.053)	(0.036)	(0.047)	(0.019)	(0.036)
II pre-demon mth. expenditures quintile	0.350***	-0.122***	-0.039	0.058***	0.051
	(0.043)	(0.036)	(0.040)	(0.018)	(0.034)
III pre-demon mth. expenditures quintile	0.313***	-0.056*	0.052	0.038**	0.058*
	(0.042)	(0.034)	(0.039)	(0.016)	(0.031)
IV pre-demon mth. expenditures quintile	0.234***	-0.020	0.098***	0.009	0.047*
	(0.032)	(0.032)	(0.027)	(0.015)	(0.024)
Controls :					
Household FE	Y	Y	Y	Y	Y
Year-month by District FE	Y	Y	Y	Y	Y
HH Size and Earning Member FE	Y	Y	Y	Y	Y
Months from Interview FE	Y	Y	Y	Y	Y
Household characteristics ($\times$ I_{During}&I_{Post})	Y	Y	Y	Y	Y
Households	144,117	144,117	144,117	144,117	144,117
Months (unbalanced)	40	40	40	40	40
Observations	4,804,111	4,804,111	4,804,111	4,804,111	4,804,111
r2	0.696	0.587	0.544	0.577	0.542

Summary & Notes: This table replicates the specification of column (5) of Table 11, swapping overall monthly household income with notable sources of income. Of interest, wages, which represent the overwhelming majority source of income, exhibits similar pattterns as seen in Table 11. Also of interest is the positive and significant increases from lower quintiles in private transfers. Household quintiles have negative or insignificant associations with other income sources. Household characteristics include a rural indicator, mean years of schooling of members 25 and older, mean age, the number of members under 14 years of age, and separate indicators for religion and caste.Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.
† The mean by months of households in the panel is 34.79.

Appendix Tables and Figures
Online Only

A Additional District Estimates

Results from the district level lights estimation in Table 2 remain robust to a number of additional tests. Table A.1 follows the estimation of column (5) of Table 2 while including a number of lags to the natural log of rainfall. Table A.2 adds an extra year to the pre-period by extending the sample to 2014. Table A.3 omits cells with no lights in 2015 to measure the intensive change to nighttime lights from demonetization. Table A.4 examines the effects of longer term deposit growth (i.e., 2016q3-2017q1). Table A.5 replaces the log-level of night lights with the monthly growth rate of nighttime lights. Table A.6 examines the growth rate in the intensive margin of lights, combining estimation strategies from Tables A.3 and A.3, and Table A.7 combines the estimations of Tables A.5 and A.4. Taken together, these additional estimates support our primary hypothesis that districts more exposed to demonetization had relative improvements in output (proxied by night lights) in the months following demonetization.

Table A.1: Rain Lags

Dependent variable: ln of monthly night time lights, Jan. 2015 - April 2018				
Rain Lags	0 (base)	3 mos.	6 mos.	12 mos.
	(1)	(2)	(3)	(4)
$I_{During}\times$ Deposit Growth, 2016q3-2016q4	-0.316*	-0.340**	-0.340**	-0.341**
	(0.168)	(0.167)	(0.167)	(0.167)
$I_{Post}\times$ Deposit Growth, 2016q3-2016q4	0.565***	0.566***	0.566***	0.565***
	(0.114)	(0.113)	(0.113)	(0.113)
Controls:				
ln Cloud Free Days	Y	Y	Y	Y
ln Population 2011 × During & Post	Y	Y	Y	Y
Geoclimatic Controls × During & Post	Y	Y	Y	Y
District FE	Y	Y	Y	Y
State-year-month FE	Y	Y	Y	Y
Districts	625	625	625	625
Months	40	40	40	40
Observations	25000	25000	25000	25000
r2	0.951	0.951	0.951	0.951

Summary & Notes: This table re-estimates the base analysis of column (5) of Table 2 while including a varying number of lags to the natural log of rainfall. The inclusion of these lags does not alter our estimates of interest. Sets of controls are listed in Table 2. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

Table A.2: Base estimation including 2014

	Dependent variable: ln of monthly night time lights, Jan. 2015 - April 2018				
	(1)	(2)	(3)	(4)	(5)
$I_{During}\times$ Deposit Growth, 2016q3-2016q4	-0.684***	-0.686***	-0.381**	-0.688***	-0.384**
	(0.212)	(0.213)	(0.154)	(0.213)	(0.154)
$I_{Post}\times$ Deposit Growth, 2016q3-2016q4	0.555***	0.596***	0.415***	0.597***	0.416***
	(0.135)	(0.137)	(0.119)	(0.136)	(0.119)
Controls:					
ln Cloud Free Days		Y	Y	Y	Y
ln Population 2011 $\times$ During & Post			Y		Y
Geoclimatic Controls $\times$ During & Post				Y	Y
ln Monthly Rainfall				Y	Y
District FE	Y	Y	Y	Y	Y
State-year-month FE	Y	Y	Y	Y	Y
Districts	625	625	625	625	625
Months	52	52	52	52	52
Observations	32500	32500	32500	32500	32500
r2	0.944	0.947	0.948	0.947	0.948

Summary & Notes: This table re-estimates the base analysis of Table 2 while extending the sample period back one year to 2014. Sets of controls are listed in Table 2. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

Table A.3: Base estimation using only 2015 lit areas (Intensive margin)

Dependent variable: ln of masked monthly night time lights, Jan. 2015 - April 2018	(1)	(2)	(3)	(4)	(5)
$I_{During}\times$ Deposit Growth, 2016q3-2016q4	-0.148	-0.150	-0.102	-0.154	-0.106
	(0.122)	(0.124)	(0.122)	(0.125)	(0.122)
$I_{Post}\times$ Deposit Growth, 2016q3-2016q4	0.239^{**}	0.287^{**}	0.215^{*}	0.289^{**}	0.217^{**}
	(0.120)	(0.120)	(0.110)	(0.120)	(0.110)
Controls:					
ln Cloud Free Days		Y	Y	Y	Y
ln Population 2011 × During & Post			Y		Y
Geoclimatic Controls × During & Post				Y	Y
ln Monthly Rainfall				Y	Y
District FE	Y	Y	Y	Y	Y
State-year-month FE	Y	Y	Y	Y	Y
Districts	625	625	625	625	625
Months	40	40	40	40	40
Observations	25000	25000	25000	25000	25000
r2	0.975	0.977	0.977	0.977	0.977

Summary & Notes: This table re-estimates the base analysis of Table 2, replacing the unsaturated nighttime lights measure with a measure of nighttime lights that only covers areas which were lit in 2015, effectively testing on the intensive margin. Sets of controls are listed in Table 2. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

Table A.4: Longer Change in Deposits: 2016q3-2017q1

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: ln of monthly night time lights, Jan. 2015 - April 2018				
$I_{During} \times$ Deposit Growth, 2016q3-2017q1	-0.544***	-0.574***	-0.337**	-0.576***	-0.338**
	(0.174)	(0.176)	(0.147)	(0.176)	(0.146)
$I_{Post} \times$ Deposit Growth, 2016q3-2017q1	0.322**	0.341***	0.219*	0.342***	0.220*
	(0.133)	(0.129)	(0.118)	(0.129)	(0.118)
Controls:					
ln Cloud Free Days		Y	Y	Y	Y
ln Population 2011 $\times$ During & Post			Y		Y
Geoclimatic Controls $\times$ During & Post				Y	Y
ln Monthly Rainfall				Y	Y
District FE	Y	Y	Y	Y	Y
State-year-month FE	Y	Y	Y	Y	Y
Districts	625	625	625	625	625
Months	40	40	40	40	40
Observations	25000	25000	25000	25000	25000
r2	0.944	0.948	0.950	0.948	0.950

Summary & Notes: This table re-estimates the base analysis of Table 2, replacing the growth in deposits between quarters 3 and 4 of 2016 with the longer run growth rate between quarter 3 of 2016 and quarter 1 of 2017. Sets of controls are listed in Table 2. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

Table A.5: Monthly growth rate of lights

Dependent variable: monthly growth rate of night time lights, Jan. 2015 - April 2018						
	(1)	(2)	(3)	(4)	(5)	(6)
$I_{During}\times$ Deposit Growth, 2016q3-2016q4	-0.507***	-0.509***	-0.351***	-0.510***	-0.353***	
	(0.111)	(0.115)	(0.105)	(0.115)	(0.105)	
$I_{Post}\times$ Deposit Growth, 2016q3-2016q4	0.089***	0.133***	0.108***	0.133***	0.109***	
	(0.019)	(0.024)	(0.020)	(0.024)	(0.020)	
Controls:						
ln Cloud Free Days		Y	Y	Y	Y	
ln Population 2011 × During & Post			Y		Y	
Geoclimatic Controls × During & Post				Y	Y	
ln Monthly Rainfall				Y	Y	
District FE	Y	Y	Y	Y	Y	
State-year-month FE	Y	Y	Y	Y	Y	
Districts	625	625	625	625	625	
Months	40	40	40	40	40	
Observations	25000	25000	25000	25000	25000	
r2	0.529	0.549	0.550	0.549	0.550	

Summary & Notes: This table re-estimates the base analysis of Table 2, replacing the natural log of the level of nighttime lights with the month-to-month growth rate of nighttime lights. Sets of controls are listed in Table 2. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

Table A.6: Monthly growth rate of lights along the intensive margin (2015 lit areas)

Dependent variable: monthly growth rate of masked lights, Jan. 2015 - April 2018	(1)	(2)	(3)	(4)	(5)
$I_{During}\times$ Deposit Growth, 2016q3-2016q4	-0.096	-0.097	-0.074	-0.098	-0.075
	(0.093)	(0.094)	(0.091)	(0.094)	(0.092)
$I_{Post}\times$ Deposit Growth, 2016q3-2016q4	0.042***	0.090***	0.085***	0.090***	0.086***
	(0.011)	(0.017)	(0.017)	(0.017)	(0.017)
Controls:					
ln Cloud Free Days		Y	Y	Y	Y
ln Population 2011 × During & Post			Y		Y
Geoclimatic Controls × During & Post				Y	Y
ln Monthly Rainfall				Y	Y
District FE	Y	Y	Y	Y	Y
State-year-month FE	Y	Y	Y	Y	Y
Districts	625	625	625	625	625
Months	40	40	40	40	40
Observations	25000	25000	25000	25000	25000
r2	0.502	0.528	0.528	0.528	0.528

Summary & Notes: This table combines the extensions of Table A.5 and Table A.3, replacing our primary outcome with the monthly growth rate of lights only in those areas that were already lit in 2015, i.e. along an intensive margin. Sets of controls are listed in Table 2. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

Table A.7: Growth rate of lights and longer deposit growth

Dependent variable: monthly growth rate of night time lights, Jan. 2015 - April 2018					
	(1)	(2)	(3)	(4)	(5)
$I_{During} \times$ Deposit Growth, 2016q3-2017q1	-0.362***	-0.393***	-0.277**	-0.394***	-0.278**
	(0.118)	(0.122)	(0.115)	(0.122)	(0.115)
$I_{Post} \times$ Deposit Growth, 2016q3-2017q1	0.073***	0.092***	0.074***	0.093***	0.074***
	(0.015)	(0.018)	(0.017)	(0.018)	(0.017)
Controls:					
ln Cloud Free Days		Y	Y	Y	Y
ln Population 2011 × During & Post			Y		Y
Geoclimatic Controls × During & Post				Y	Y
ln Monthly Rainfall				Y	Y
District FE	Y	Y	Y	Y	Y
State-year-month FE	Y	Y	Y	Y	Y
Districts	625	625	625	625	625
Months	40	40	40	40	40
Observations	25000	25000	25000	25000	25000
r2	0.529	0.549	0.550	0.549	0.550

Summary & Notes: This table combines the extensions of Table A.5 and Table A.4, regressing the monthly growth rate of nighttime lights on the longer run growth in deposits interacted with during and post demonetization indicators. Sets of controls are listed in Table 2. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

B Additional Household Summary Statistics

Table B.1: Expenditure Summary Statistics (I) For Table 9

	All Periods Jan. 2015 - Apr. 2018	Pre Jan. 2015 - Oct. 2016	During Nov. 2016 - Dec. 2016	Post Jan. 2017 - Apr. 2018
Monthly Real Expenditures, Food (in 100s of ₹)	37.19	37.45	34.64	37.14
	(15.23)	(14.63)	(15.05)	(16.05)
Quintile 1	25.84	24.94	24.92	27.27
	(9.65)	(8.10)	(10.69)	(11.27)
Quintile 2	32.34	31.99	30.48	33.09
	(10.22)	(8.63)	(11.20)	(12.00)
Quintile 3	36.74	36.89	34.33	36.83
	(11.23)	(9.84)	(12.08)	(12.86)
Quintile 4	41.72	42.50	38.86	40.94
	(13.02)	(11.54)	(13.48)	(14.78)
Quintile 5	50.71	52.54	45.98	48.67
	(18.58)	(17.25)	(18.33)	(20.08)
Monthly Real Expenditures, Clothes (in 100s of ₹)	4.35	4.18	3.72	4.69
	(12.80)	(12.14)	(8.58)	(14.12)
Quintile 1	2.39	1.96	2.43	3.02
	(7.60)	(4.51)	(6.27)	(10.69)
Quintile 2	3.24	2.85	3.08	3.82
	(8.69)	(6.44)	(6.69)	(11.34)
Quintile 3	3.79	3.55	3.35	4.20
	(7.76)	(7.16)	(7.82)	(8.55)
Quintile 4	4.78	4.63	4.04	5.08
	(12.41)	(9.64)	(9.06)	(15.89)
Quintile 5	7.95	8.33	6.00	7.65
	(22.15)	(23.54)	(11.93)	(21.06)
Monthly Real Expenditures, Cosmetics (in 100s of ₹)	4.77	4.74	4.39	4.86
	(2.82)	(2.78)	(2.57)	(2.89)
Quintile 1	3.13	2.94	3.04	3.43
	(1.64)	(1.49)	(1.59)	(1.81)
Quintile 2	3.95	3.81	3.70	4.17
	(1.91)	(1.79)	(1.77)	(2.06)
Quintile 3	4.57	4.54	4.22	4.65
	(2.15)	(2.09)	(1.99)	(2.24)
Quintile 4	5.39	5.44	4.95	5.36
	(2.55)	(2.46)	(2.38)	(2.70)
Quintile 5	7.05	7.22	6.25	6.90
	(3.83)	(3.68)	(3.58)	(4.04)

Table B.2: Expenditure Summary Statistics (II) For Table 9

	All Periods Jan. 2015 - Apr. 2018	Pre Jan. 2015 - Oct. 2016	During Nov. 2016 - Dec. 2016	Post Jan. 2017 - Apr. 2018
Monthly Real Expenditures, Rent (in 100s of ₹)	0.86	0.88	0.83	0.83
	(3.44)	(3.67)	(3.06)	(3.12)
Quintile 1	0.38	0.35	0.39	0.42
	(1.49)	(1.46)	(1.42)	(1.55)
Quintile 2	0.55	0.53	0.57	0.59
	(2.12)	(2.12)	(2.06)	(2.13)
Quintile 3	0.68	0.68	0.68	0.68
	(2.60)	(2.67)	(2.50)	(2.50)
Quintile 4	0.93	0.97	0.93	0.88
	(3.44)	(3.66)	(3.28)	(3.13)
Quintile 5	1.85	1.99	1.67	1.69
	(5.92)	(6.48)	(4.95)	(5.14)
Monthly Real Expenditures, Power (in 100s of ₹)	12.20	11.64	11.33	13.13
	(10.03)	(9.67)	(9.40)	(10.54)
Quintile 1	6.32	5.57	6.12	7.44
	(4.46)	(3.72)	(4.21)	(5.20)
Quintile 2	8.78	8.05	8.29	9.92
	(5.67)	(4.89)	(5.27)	(6.52)
Quintile 3	10.88	10.20	10.22	11.97
	(6.70)	(6.01)	(6.38)	(7.52)
Quintile 4	14.10	13.51	13.14	15.09
	(8.33)	(7.55)	(7.93)	(9.33)
Quintile 5	21.94	21.99	19.97	22.13
	(14.59)	(14.09)	(14.15)	(15.32)
Monthly Real Expenditures, Transportation (in 100s of ₹)	2.10	2.12	1.98	2.08
	(4.37)	(3.95)	(4.46)	(4.91)
Quintile 1	1.42	1.34	1.36	1.54
	(1.41)	(1.33)	(1.27)	(1.53)
Quintile 2	1.69	1.65	1.62	1.76
	(2.06)	(2.14)	(2.00)	(1.94)
Quintile 3	1.90	1.91	1.79	1.89
	(2.14)	(1.79)	(1.61)	(2.61)
Quintile 4	2.27	2.36	2.13	2.17
	(3.49)	(2.27)	(3.77)	(4.70)
Quintile 5	3.34	3.47	3.17	3.18
	(8.76)	(8.15)	(9.10)	(9.53)

Table B.3: Expenditure Summary Statistics (I) For Table 10

	All Periods Jan. 2015 - Apr. 2018	Pre Jan. 2015 - Oct. 2016	During Nov. 2016 - Dec. 2016	Post Jan. 2017 - Apr. 2018
Monthly Real Expenditures, Appliances (in 100s of ₹)	0.67	0.51	0.58	0.92
	(4.37)	(3.61)	(3.73)	(5.35)
Quintile 1	0.28	0.16	0.29	0.44
	(1.72)	(0.98)	(1.42)	(2.43)
Quintile 2	0.38	0.23	0.40	0.60
	(2.60)	(1.56)	(2.69)	(3.59)
Quintile 3	0.48	0.34	0.45	0.69
	(2.78)	(1.89)	(2.61)	(3.73)
Quintile 4	0.71	0.55	0.59	0.96
	(3.87)	(2.68)	(3.62)	(5.15)
Quintile 5	1.61	1.36	1.25	2.01
	(8.21)	(7.41)	(6.58)	(9.41)
Monthly Real Expenditures, Intoxicants (in 100s of ₹)	2.44	2.38	2.28	2.55
	(2.83)	(2.80)	(2.79)	(2.87)
Quintile 1	1.67	1.53	1.54	1.88
	(1.93)	(1.75)	(1.87)	(2.17)
Quintile 2	2.07	2.00	1.87	2.20
	(2.25)	(2.17)	(2.24)	(2.37)
Quintile 3	2.48	2.42	2.28	2.58
	(2.58)	(2.54)	(2.52)	(2.65)
Quintile 4	2.85	2.78	2.75	2.96
	(2.99)	(2.96)	(3.02)	(3.03)
Quintile 5	3.21	3.23	3.07	3.18
	(3.86)	(3.92)	(3.76)	(3.79)
Monthly Real Expenditures, Recreation (in 100s of ₹)	0.44	0.38	0.35	0.54
	(2.06)	(1.54)	(1.57)	(2.68)
Quintile 1	0.20	0.12	0.16	0.33
	(1.06)	(0.58)	(0.74)	(1.52)
Quintile 2	0.27	0.19	0.22	0.40
	(1.30)	(0.79)	(0.95)	(1.83)
Quintile 3	0.32	0.25	0.25	0.42
	(1.32)	(1.20)	(1.04)	(1.50)
Quintile 4	0.46	0.42	0.34	0.55
	(2.85)	(1.55)	(1.25)	(4.17)
Quintile 5	1.01	0.98	0.83	1.08
	(2.94)	(2.66)	(2.96)	(3.29)

Table B.4: Expenditure Summary Statistics (II) for Table 10

	All Periods Jan. 2015 - Apr. 2018	Pre Jan. 2015 - Oct. 2016	During Nov. 2016 - Dec. 2016	Post Jan. 2017 - Apr. 2018
Monthly Real Expenditures, Restaurants (in 100s of ₹)	1.40	1.43	1.15	1.39
	(2.14)	(2.16)	(1.73)	(2.16)
Quintile 1	0.75	0.65	0.70	0.89
	(1.01)	(0.97)	(0.97)	(1.05)
Quintile 2	0.99	0.97	0.88	1.04
	(1.25)	(1.24)	(1.20)	(1.27)
Quintile 3	1.17	1.20	0.99	1.15
	(1.51)	(1.50)	(1.33)	(1.56)
Quintile 4	1.48	1.53	1.22	1.43
	(1.91)	(1.85)	(1.52)	(2.03)
Quintile 5	2.76	2.96	2.08	2.57
	(3.61)	(3.62)	(2.82)	(3.65)
Monthly Real Expenditures, Vehicle EMI (in 100s of ₹)	0.30	0.17	0.23	0.51
	(4.04)	(3.46)	(3.08)	(4.85)
Quintile 1	0.10	0.03	0.04	0.22
	(2.90)	(1.57)	(1.04)	(4.25)
Quintile 2	0.16	0.05	0.10	0.31
	(2.19)	(1.60)	(1.79)	(2.88)
Quintile 3	0.19	0.07	0.15	0.38
	(2.80)	(1.84)	(2.84)	(3.77)
Quintile 4	0.30	0.14	0.24	0.53
	(3.54)	(2.34)	(3.33)	(4.80)
Quintile 5	0.82	0.58	0.65	1.19
	(7.19)	(7.07)	(5.09)	(7.59)
Monthly Real Expenditures, Durable EMI (in 100s of ₹)	0.06	0.03	0.04	0.12
	(1.81)	(1.56)	(1.66)	(2.13)
Quintile 1	0.03	0.01	0.01	0.06
	(0.75)	(0.30)	(0.59)	(1.14)
Quintile 2	0.04	0.01	0.04	0.09
	(0.84)	(0.44)	(0.78)	(1.22)
Quintile 3	0.05	0.02	0.05	0.11
	(1.07)	(0.60)	(1.95)	(1.40)
Quintile 4	0.07	0.03	0.03	0.13
	(1.91)	(0.95)	(0.98)	(2.82)
Quintile 5	0.13	0.08	0.07	0.20
	(3.34)	(3.41)	(2.97)	(3.27)

Table B.5: Sources of Income Summary Statistics (I)

	All Periods Jan. 2015 - Apr. 2018	Pre Jan. 2015 - Oct. 2016	During Nov. 2016 - Dec. 2016	Post Jan. 2017 - Apr. 2018
Monthly Real Income, Wages (in 100s of ₹)	115.58	111.87	110.96	121.60
	(126.19)	(116.02)	(117.53)	(140.51)
Quintile 1	65.87	59.41	66.54	75.24
	(58.38)	(48.16)	(53.18)	(70.22)
Quintile 2	86.53	81.46	84.65	94.19
	(73.40)	(64.69)	(65.78)	(84.79)
Quintile 3	101.79	97.55	97.60	108.54
	(91.16)	(81.59)	(80.86)	(104.36)
Quintile 4	128.93	125.99	122.36	134.07
	(124.26)	(111.29)	(110.55)	(142.39)
Quintile 5	204.30	205.20	193.77	204.35
	(197.38)	(179.10)	(192.33)	(221.76)
Monthly Real Income, Business (in 100s of ₹)	5.44	1.78	2.86	11.13
	(39.86)	(23.01)	(24.54)	(56.69)
Quintile 1	1.28	0.15	0.21	3.08
	(12.50)	(4.27)	(4.92)	(19.25)
Quintile 2	2.43	0.34	0.64	5.74
	(19.10)	(7.38)	(9.00)	(28.96)
Quintile 3	3.45	0.76	1.46	7.65
	(25.71)	(12.80)	(15.78)	(37.61)
Quintile 4	6.23	1.94	4.13	12.77
	(38.79)	(20.35)	(28.26)	(55.83)
Quintile 5	14.83	6.21	8.61	28.14
	(74.77)	(46.44)	(44.59)	(103.66)
Monthly Real Income, Govt. Transfers (in 100s of ₹)	0.54	0.30	0.33	0.91
	(3.53)	(3.17)	(2.71)	(4.07)
Quintile 1	0.54	0.27	0.27	0.97
	(2.75)	(2.46)	(2.28)	(3.13)
Quintile 2	0.50	0.24	0.27	0.91
	(2.82)	(2.32)	(2.08)	(3.46)
Quintile 3	0.48	0.26	0.29	0.83
	(3.28)	(2.89)	(2.18)	(3.85)
Quintile 4	0.50	0.26	0.33	0.87
	(3.41)	(2.73)	(3.20)	(4.21)
Quintile 5	0.68	0.49	0.50	0.97
	(5.10)	(4.95)	(3.61)	(5.45)

Table B.6: Sources of Income Summary Statistics (II)

	All Periods Jan. 2015 - Apr. 2018	Pre Jan. 2015 - Oct. 2016	During Nov. 2016 - Dec. 2016	Post Jan. 2017 - Apr. 2018
Monthly Real Income, Priv. Transfers (in 100s of ₹)	1.40	1.09	1.20	1.87
	(11.96)	(11.20)	(10.02)	(13.19)
Quintile 1	1.76	1.31	1.69	2.43
	(9.08)	(7.46)	(8.35)	(11.07)
Quintile 2	1.13	0.75	1.04	1.70
	(9.06)	(7.50)	(8.58)	(10.98)
Quintile 3	0.98	0.69	0.78	1.42
	(9.49)	(8.04)	(7.88)	(11.44)
Quintile 4	1.17	0.91	0.94	1.60
	(11.75)	(10.56)	(9.53)	(13.51)
Quintile 5	2.03	1.92	1.61	2.24
	(18.55)	(19.10)	(14.83)	(18.16)
Monthly Real Income, Imputed (in 100s of ₹)	1.04	0.64	0.73	1.66
	(8.45)	(6.77)	(9.29)	(10.30)
Quintile 1	0.99	0.75	0.67	1.40
	(9.99)	(10.67)	(9.12)	(9.02)
Quintile 2	0.92	0.50	0.59	1.58
	(6.76)	(5.30)	(6.02)	(8.49)
Quintile 3	1.02	0.58	0.67	1.71
	(6.46)	(4.42)	(4.85)	(8.72)
Quintile 4	1.11	0.66	0.84	1.79
	(6.90)	(4.92)	(5.55)	(9.12)
Quintile 5	1.18	0.75	0.92	1.83
	(11.38)	(6.74)	(16.78)	(15.19)

C Additional Mechanism: Credit

Our primary way of measuring the spatial intensity of demonetization is to use the increase in banking deposits as shown in Figure 2. While banks were initially flush with deposits, these were obviously temporary. This is seen by the immediate outflow of deposits the quarter after demonetization in the same figure. Given this short term influx of available funds, banks would not be incentivized to make longer term loans.[58]

What is of greater interest is whether there could be medium term effects of district variation in the influx of deposits, i.e. individuals did not feel the need to withdraw all of their deposits and the government was thus possibly partly successful in channeling cash back into the formal banking system. Also, if a portion of the deposits could be attributed to the redistribution channel, there is even less reason for all deposits to be withdrawn. Figure 2 suggests that these might have been at play. To better account for this longer term increase in deposits and any potential effects on credit, we again perform a DD estimation.

We first examine the relationship between our primary measure of deposit growth from demonetization and district-level credit in Table C.1. In other words, we replicate Table 2, replacing the natural log of monthly nighttime lights with the natural log of quarterly credit. Doing so results in a marginally significant (i.e., $p<0.10$) positive association between district deposit growth and the level of outstanding credit following demonetization; no significant effect is observed in the quarter of demonetization. For the baseline specification (col. 5), a standard deviation increase in deposit growth is associated with 1.5% increase in outstanding credit. Figure C.1 plots quarterly effects. As seen, there appears to be a positive trend in credit prior to demonetization, followed by a clear increase in effects after demonetization.

A more appropriate measure of deposit change accounts for the longer term increase in deposits that resulted from demonetization - the growth in deposits between Q3 2016 and Q1 2017. The longer term measure of deposit change is considered in Table C.2 and Figure C.2. As shown, we estimate no changes to credit associated with this longer term deposit growth during demonetization, but in the quarters after, we observe a statistically significant increase in credit. In other words, districts that had longer-term increases in deposits also had increases in credit. In particular, the estimates of Table C.2 suggest a one

[58] Indeed, the Reserve Bank of India (RBI) required this initial influx of deposits to be held as reserves, requiring all additional deposits between September 16^{th} and November 11^{th} to be held as reserves. To compensate interest paid on deposits, however, the 100% reserve ratio period was ended and followed by the RBI issuing short-term debt (Chodorow-Reich et al., 2020). As a result of these actions, the stock of money (i.e., M3) remained relatively constant (Figure **??**)

standard deviation increase in longer run deposit growth is again associated with a ≈1.5% quarterly increase in credit following demonetization. The quarterly effects in Figure C.2 again show potential pre-trends in credit and districts that experienced larger long-term deposit growth, but there is a clear increase following demonetization that is absent in the pre-period.

To test pre-trends in credit from district deposit growth from demonetization, Table C.3 tests for linear trends in credit prior to demonetization by district deposit growth, both our primary measure (Panel A) and longer term deposit growth (Panel B). The findings of Table C.3 suggest differential pre-trends in credit tied to the shorter term deposit growth from demonetization in Panel A, but there is not sufficient evidence in Panel B to suggest statistically significant linear trend differences in credit tied to the longer term measure of deposit growth. However, the lack of parallel trends in credit prior to demonetization appear to be an obvious problem Figures C.1 and C.2. Nevertheless it does not completely refute our hypothesis. First, most banks in India are state owned, and credit often follows state directed priorities such as lending to agriculture and small scale industry on lenient terms, over and above meeting targets to these and other priority sectors. Cole (2009) also notes that agricultural credit tends to follow election cycles. Gupta et al (2015) note that, despite the removal of various restrictions since the onset of economic reforms in 1991, banks have continued to lend to state governments and state operated entities. Given this backdrop, it is not surprising that while we do see a significant effect, the parallel trends assumption is questionable.

Table C.1: Credit Post Demonetization

Dependent variable: ln of quarterly credit, Q1 2015 - Q1 2018	(1)	(2)	(3)	(4)	(5)
$I_{During} \times$ Dep. Growth, 2016q3-2016q4	0.044	0.044	0.022	0.060	0.033
	(0.061)	(0.061)	(0.059)	(0.055)	(0.052)
$I_{Post} \times$ Dep. Growth, 2016q3-2016q4	0.259*	0.259*	0.190	0.292**	0.207*
	(0.149)	(0.149)	(0.137)	(0.139)	(0.124)
Controls:					
ln Cloud Free Days (quarterly avg.)		Y	Y	Y	Y
ln Population 2011 $\times$ During & Post			Y		Y
Geoclimatic Controls $\times$ During & Post				Y	Y
ln Rainfall (quarterly avg.)				Y	Y
District FE	Y	Y	Y	Y	Y
State-year-quarter FE	Y	Y	Y	Y	Y
Districts	625	625	625	625	625
Quarters†	13	13	13	13	13
Observations	8124	8124	8124	8124	8124
R Sqr.	0.995	0.995	0.995	0.995	0.995

Summary & Notes: This table estimates the during/post differences in the natural log of district level credit with the longer run change in deposits from demonetization. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.
† Data for 2016q1 is missing for Khammam.

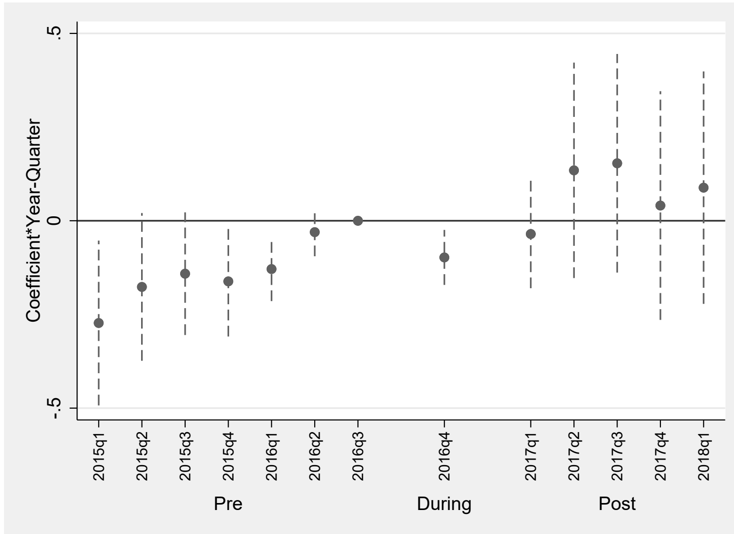


Figure C.1: Credit by Quarter: Deposit Growth (2016q3-2016q4)

Summary & Notes: This figure plots the quarterly relationship between the natural log of district-level credit and deposit growth from demonetization. As shown, deposit growth, which serves as a proxy for the intensity of demonetization, has a close to negative or zero effect prior to demonetization (2016q4) but a positive effect in the months after demonetization.

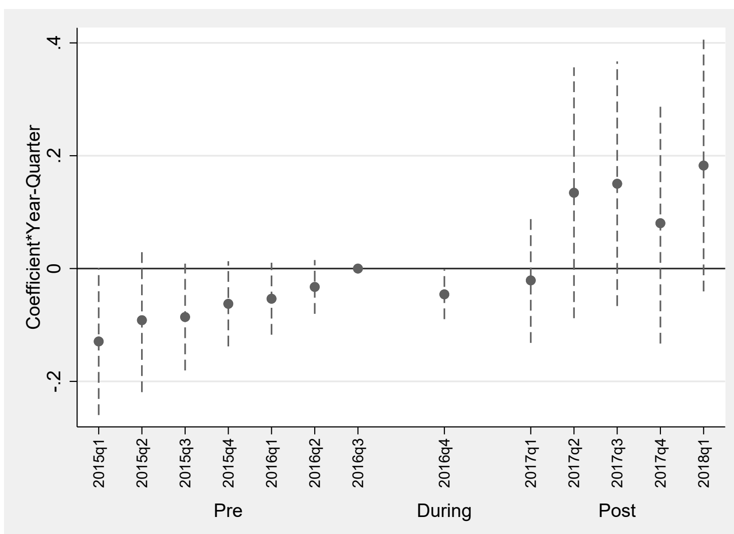


Figure C.2: Credit by Quarter: Long Deposit Growth (2016q3-2017q1)

Summary & Notes: This figure plots the quarterly relationship between the natural log of district-level credit and longer run (2016q3-2017q1) deposit growth from demonetization. As shown, deposit growth, which serves as a proxy for the intensity of demonetization, has a close to zero effect prior to demonetization (2016q4) but a positive effect in the months after demonetization.

Table C.2: Credit Post Demonetization

	(1)	(2)	(3)	(4)	(5)
	Dependent variable: ln of quarterly credit, Q1 2015 - Q1 2018				
$I_{During}\times$ Dep. Growth, 2016q3-2017q1	0.039	0.037	0.021	0.036	0.019
	(0.046)	(0.046)	(0.048)	(0.038)	(0.039)
$I_{Post}\times$ Dep. Growth, 2016q3-2017q1	0.222**	0.222**	0.171*	0.221**	0.170*
	(0.105)	(0.105)	(0.094)	(0.101)	(0.088)
Controls:					
ln Cloud Free Days (quarterly avg.)		Y	Y	Y	Y
ln Population 2011 × During & Post			Y		Y
Geoclimatic Controls × During & Post				Y	Y
ln Rainfall (quarterly avg.)				Y	Y
District FE	Y	Y	Y	Y	Y
State-year-quarter FE	Y	Y	Y	Y	Y
Districts	625	625	625	625	625
Quarters†	13	13	13	13	13
Observations	8124	8124	8124	8124	8124
R Sqr.	0.995	0.995	0.995	0.995	0.995

Summary & Notes: This table estimates the during/post differences in the natural log of district level credit with the longer run change in deposits from demonetization. Standard errors are clustered by district, and statistical signficance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.
† Data for 2016q1 is missing for Khammam.

Table C.3: Pre-Trends in Credit

	Dependent variable: ln of quarterly credit, Q1 2015 - Q3 2016				
	(1)	(2)	(3)	(4)	(5)
Panel A: Deposit Growth, 2016q3-2016q4					
Trend × Deposit Growth, 2016q3-2016q4	0.030***	0.032**	0.028**	0.035**	0.032**
	(0.011)	(0.014)	(0.014)	(0.014)	(0.014)
Trend	0.030***	0.041***	0.075***	0.055***	0.076***
	(0.002)	(0.003)	(0.018)	(0.015)	(0.024)
Controls:					
ln Quarterly Cloud Free Days		Y	Y	Y	Y
ln Population 2011 × Trend			Y		Y
Geoclimatic Controls × Trend				Y	Y
ln Quarterly Rainfall				Y	Y
District FE	Y	Y	Y	Y	Y
State trends	N	Y	Y	Y	Y
Observations	6874	6874	6874	6874	6874
r2	0.998	0.999	0.999	0.999	0.999
Panel B: Longer Term Deposit Growth, 2016q3-2017q1					
Trend × Dep. Growth, 2016q3-2017q1	0.032***	0.012	0.009	0.012	0.010
	(0.006)	(0.008)	(0.008)	(0.008)	(0.008)
Trend	0.030***	0.042***	0.080***	0.061***	0.091***
	(0.001)	(0.003)	(0.017)	(0.015)	(0.024)
Controls:					
ln Quarterly Cloud Free Days		Y	Y	Y	Y
ln Population 2011 × Trend			Y		Y
Geoclimatic Controls × Trend				Y	Y
ln Quarterly Rainfall				Y	Y
District FE	Y	Y	Y	Y	Y
State trends		Y	Y	Y	Y
Observations	6874	6874	6874	6874	6874
r2	0.998	0.999	0.999	0.999	0.999

Summary & Notes: The insignificant interaction between the trend variable and the growth of deposits from demonetization is suggestive that linear trends were indeed parallel prior to treatment. Growth of Deposits is the district-level percentage change in deposits from quarter 3 to quarter 4 of 2016; a time range that captures demonetization. Standard errors are clustered by district, and statistical significance at the 1, 5, and 10% levels is respectively denoted by ***, **, and *.

D Alternative Household Specifications

D.1 Relative Effects of Q1 and Q5 to Middle Quintiles

In order to further show that the poorest (in terms of 2015 monthly expenditures) household quintile has statistically significant larger effects compared to other quintiles, Tables D.1 and D.2 replicate the estimation of Tables 8 and 11 while changing the omitted group from the top quintile to the three middle quintiles. Indeed, this alternative specification shows that the poorest quintile had relative increases to the middle quintiles when accounting for the reduction in the top quintile.

Table D.1: Household Expenditure Effects by Pre-demonetization Expenditure Quintiles: Omitting Middle Quintiles

	Dependent variable: ln Monthly Total Expenditures + 1; January 2015 - April 2018				
	(1)	(2)	(3)	(4)	(5)
$I_{During}\times$ Quintile:					
I pre-demon mth. income quintile	0.096***	0.120***	0.125***	0.101***	0.117***
	(0.019)	(0.019)	(0.020)	(0.020)	(0.022)
V pre-demon mth. income quintile	-0.105***	-0.141***	-0.145***	-0.131***	-0.144***
	(0.019)	(0.017)	(0.017)	(0.017)	(0.020)
$I_{Post}\times$ Quintile:					
I pre-demon mth. income quintile	0.132***	0.147***	0.151***	0.117***	0.146***
	(0.028)	(0.023)	(0.026)	(0.027)	(0.030)
V pre-demon mth. income quintile	-0.108***	-0.186***	-0.203***	-0.183***	-0.208***
	(0.023)	(0.027)	(0.024)	(0.024)	(0.028)
Controls:					
Household FE	Y	Y	Y	Y	Y
Year-month FE	Y				
Year-month by State FE		Y			
Year-month by District FE			Y	Y	Y
HH Size and Earning Member FE				Y	Y
Months from Interview FE				Y	Y
Household characteristics ($\times$ I_{During}&I_{Post})					Y
Households	144,117	144,117	144,117	144,117	144,117
Months (unbalanced)	40	40	40	40	40
Observations	4,804,111	4,804,111	4,804,111	4,804,111	4,804,111
r2	0.402	0.504	0.562	0.572	0.573

Summary & Notes: This table replicates Table 8, omitting quintiles 2, 3, and 4 in place of quintile 5. Estimates show that lowest quintile had statistically significant positive effects relative to the middle quintiles, further suggesting relative improvements among the poorest households. Household characteristics include a rural indicator, years of schooling, mean age, the number of members under 14 years of age, and separate indicators for religion and caste.

Table D.2: Household Income Effects by Pre-demonetization Expenditure Quintiles: Omitting Middle Quintiles

	Dependent variable: ln Monthly Total Income + 1; January 2015 - April 2018				
	(1)	(2)	(3)	(4)	(5)
$I_{During} \times$ Quintile:					
I pre-demon mth. income quintile	0.099***	0.125***	0.110***	0.062***	0.056**
	(0.023)	(0.019)	(0.019)	(0.020)	(0.022)
V pre-demon mth. income quintile	-0.104***	-0.121***	-0.126***	-0.093***	-0.094***
	(0.026)	(0.027)	(0.022)	(0.021)	(0.022)
$I_{Post} \times$ Quintile:					
I pre-demon mth. income quintile	0.082**	0.126***	0.127***	0.070***	0.072**
	(0.032)	(0.023)	(0.025)	(0.025)	(0.028)
V pre-demon mth. income quintile	-0.103***	-0.194***	-0.201***	-0.153***	-0.167***
	(0.025)	(0.032)	(0.027)	(0.026)	(0.030)
Controls:					
Household FE	Y	Y	Y	Y	Y
Year-month FE	Y				
Year-month by State FE		Y			
Year-month by District FE			Y	Y	Y
HH Size and Earning Member FE				Y	Y
Months from Interview FE				Y	Y
Household characteristics ($\times$ I_{During}&I_{Post})					Y
Households	144,117	144,117	144,117	144,117	144,117
Months (unbalanced)	40	40	40	40	40
Observations	4,804,111	4,804,111	4,804,111	4,804,111	4,804,111
r2	0.337	0.367	0.422	0.446	0.447

Summary & Notes: This table replicates Table 11, omitting quintiles 2, 3, and 4 in place of quintile 5. Estimates show that lowest quintile had statistically significant positive effects relative to the middle quintiles, further suggesting relative improvements among the poorest households. Household characteristics include a rural indicator, years of schooling, mean age, the number of members under 14 years of age, and separate indicators for religion and caste.