CASH AND THE ECONOMY:
EVIDENCE FROM INDIA'S DEMONETIZATION

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ABSTRACT

We analyze a unique episode in the history of monetary economics, the 2016 Indian "demonetization." This policy made 86% of cash in circulation illegal tender overnight, with new notes gradually introduced over the next several months. We present a model of demonetization where agents hold cash both to satisfy a cash-in-advance constraint and for tax evasion purposes. We test the predictions of the model in the cross-section of Indian districts using several novel data sets including: a data set containing the geographic distribution of demonetized and new notes for causal inference; nightlights data and employment surveys to measure economic activity including in the informal sector; debit/credit cards and e-wallet transactions data; and banking data on deposit and credit growth. Districts experiencing more severe demonetization had relative reductions in economic activity, faster adoption of alternative payment technologies, and lower bank credit growth. The cross-sectional responses cumulate to a contraction in employment and nightlights-based output due to demonetization of 2 p.p. and of bank credit of 2 p.p. in 2016Q4 relative to their counterfactual paths, effects which dissipate over the next few months. We use our model to show these cumulated effects are a lower bound for the aggregate effects of demonetization. We conclude that unlike in the cashless limit of new-Keynesian models, in modern India cash serves an essential role in facilitating economic activity.

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1 Introduction

Cash can serve an essential role and raise welfare by overcoming frictions in transactions such as the lack of double coincidence of wants, limited commitment, and asymmetric information. In the New Keynesian synthesis (Woodford, 2003), however, which is at the foundation of modern monetary policy making, money only serves as a unit of account. In this so-called cashless limit, outcomes depend on the interest rate set by monetary policy, with the details of the change in money supply that accompany it essentially irrelevant. Instead, cash is an inconvenience which constrains monetary policy by putting a floor on the nominal interest rate and facilitates illegal activity and tax evasion (Rogoff, 2016).

In this paper we study the importance of the transaction role of cash by analyzing a unique episode in the history of monetary economics. On November 8th, 2016, the government of India unexpectedly declared 86% of the existing currency in circulation illegal tender, effective at midnight. Referred to as "demonetization," this policy resulted in a sharp decrease in the availability of cash which could be used in transactions because printing press constraints prevented the immediate replacement of the demonetized currency with new notes. Demonetization occurred in an otherwise stable macroeconomic environment and did not affect other hallmarks of monetary policy such as the overall liabilities of the Reserve Bank of India (RBI) or the target interest rate. Thus, the experiment offers a unique opportunity to observe the importance of cash as a facilitator of transactions.

We first present a model of demonetization to translate the policy into standard economics and generate predictions. In the model, agents hold cash for two reasons. Firstly, because of a cash-in-advance (CIA) constraint requiring money holdings to pay for expenditures, along the lines of Lucas (1982), Lucas and Stokey (1987), and Svensson (1985). Secondly, because holding cash reduces the effective tax rate by facilitating tax evasion. Demonetization in the model amounts to a forced conversion of cash into less liquid bank deposits, which in the presence of downward wage rigidity generates a decline in output, employment, and borrowing by firms. Households also switch to non-cash forms of payment to attenuate the impact of the cash shortage.

We then provide empirical evidence of the effects of demonetization. National time series aggregates cannot answer this question because they have limited coverage of the informal, cash-intensive sector of the economy and because other economic shocks occurred during the period. Instead, we study the consequences of demonetization in the cross-section of Indian districts. Using a comprehensive data set from the RBI containing the geographic distribution of demonetized and new notes, we construct a local area demonetization shock

as the ratio of the arrival of new notes in an area to the quantity of demonetized notes in that area. We present both narrative and statistical evidence that variation in these demonetization shocks occurred essentially at random with respect to economic activity.

We study outcomes drawn from a number of different data sets, many of which have not previously been used in academic research. We first show that districts which experienced more severe demonetization shocks had much larger contractions in ATM withdrawals. The link between currency availability and cash withdrawals both validates the usefulness of our geographic shock measure and provides *prima facie* evidence of a cash shortfall.

We next show that demonetization had an adverse effect on real economic activity. Official data on economic activity at a subnational level and at high frequency do not exist. We use a new household survey of employment and satellite data on human-generated nightlight activity to measure demonetization's effects at the district level. Importantly, these variables capture both formal and informal sector economic activity. Both variables show economically sharp, statistically highly significant contractions in areas experiencing more severe demonetization shocks. The effects on real economic activity peak in the period immediately following the announcement and dissipate over the next few months as new currency arrives. In terms of magnitude, comparing districts at the 10th and 90th percentiles of the demonetization shock in the period immediately after the announcement, both variables map into a difference in output of roughly 4.5 percentage points.

Our third set of results show the adoption of alternative forms of payment technology. While the difference in output across districts is substantial, it is far less than the roughly 50 percentage point inter-decile difference in the amount of currency replaced. In our model, this can occur if households endogenously found ways around using money to conduct transactions, for example by switching to alternative payment methods like debit cards, credit cards, and e-wallets or by convincing retailers to open an informal line of credit or to accept old notes. We use data on the transacted value of two leading electronic payments methods, e-wallet and point-of-service cards, to show that this substitution occurred. This pattern also corroborates our identifying assumption as a confounding non-demonetization demand shock would induce comovement across all payments mechanisms and output.

Finally, we show responses in the banking sector. Areas which experienced more severe cash shortages had higher deposit growth as households could not withdraw money from their bank accounts. Credit growth in these areas also slowed, providing additional corroborating evidence of an effect on real activity.

Our results imply demonetization lowered the growth rate of economic activity by at least

2 p.p. in the quarter of demonetization. To reach this number, we first cumulate the cross-sectional effects on employment and nightlights over districts. Next, our model suggests that these cross-sectional estimates provide a lower bound for the aggregate consequences of demonetization due to cross-district trade. Combining these two results yields a decline in nightlights-based economic activity and of employment of 3 p.p. or more in November and December of 2016 relative to the the counterfactual path, which translates into a decline in the quarterly growth rate of 2 p.p. or more. Similarly, the effect on credit implies a 2 p.p. or more decline in 2016Q4.[1] We conclude that while the cashless limit may appropriately describe economies with well developed financial markets, in modern India cash continues to serve an essential role in facilitating economic activity.

We review related literature next. Section 2 contains institutional details of demonetization. Section 3 presents the model and empirical predictions. Section 4 describes the data, the construction of the geographic demonetization shocks, and the conditions for causal interpretation of the analysis. Section 5 presents the results and Section 6 discusses the aggregate implications.

Related literature. A few early studies have used descriptive statistics (RBI, 2017b; Krishnan and Siegel, 2017) or simple time series methods (Aggarwal and Narayanan, 2017; Banerjee and Kala, 2017) to infer the effect of demonetization on the Indian economy. We introduce a number of new data sets and a cross-sectional empirical approach to more credibly identify the causal effects of the policy. Methodologically, this approach relates to a burgeoning literature using cross-sectional, regional variation to study macroeconomic topics, as reviewed in Nakamura and Steinsson (2018) and Chodorow-Reich (Forthcoming). This literature has so far avoided the topic of monetary policy because monetary policy is determined at the national (or higher) level. In contrast, our setting contains large cross-regional variation in the change in money. Ramey (2016) offers a forceful critique of time series studies of the effect of money on output as restricted to studying small changes in policy. Similar to Velde (2009) who traces the effects of large, overnight diminutions of coins in 18th century France, we study a sudden and very large change in currency.

Our empirical results provide support for theoretical traditions which view money as essential in that the presence of money makes possible superior allocations. We follow Lucas (1982), Lucas and Stokey (1987), and Svensson (1985) in modeling the need for money through a cash-in-advance (CIA) constraint. The "new monetarist perspective" (Williamson

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[1]These are non-annualized numbers.

and Wright, 2010) instead introduces limited commitment and lack of double coincidence of wants to create a problem which money alleviates.[2] Agrawal (2018) provides a model of a demonetization episode in this tradition. As noted by Kocherlakota (1998), any mechanism which creates a record of transactions ("memory") can substitute for money in a new monetarist economy. We document empirically one such substitution – the switch to e-wallet and POS payments technologies. Our model incorporates such substitution through an endogenous threshold for the CIA constraint, making it immune along this dimension to an otherwise clear example of the Lucas critique (Lucas, 1976) applying.[3] In independent work, Crouzet, Gupta, and Mezzanotti (2018) also examine the adoption of alternative payment technology during demonetization and, like us, find persistent effects of demonetization on e-wallet use. Whereas their paper focuses on the network externalities of payment technologies, we emphasize the interplay between adoption of alternative means of payment and the effect on output.

Last, our paper sheds light on a policy debate around the possible benefits of moving to a cashless economy. Rogoff (2016) articulates the societal costs of cash including putting a floor on the nominal interest rate and facilitating illegal activity and tax evasion. Nonetheless, he cautions that if it occurs a phase-out of cash should take place slowly and with ample anticipation to allow households to adjust to other forms of payment. Our results accord with these prescriptions.

2 Demonetization

On November 8, 2016, at 8:15pm local time, the Prime Minister of India announced in an unscheduled national televised address that the two largest denomination notes, the 500 ($7.5) and 1000 rupee ($15) notes, would cease to be legal tender, to be replaced by new 500 and 2000 notes. Effective at midnight, holders of the old notes could deposit them at banks but could not use them in transactions. The stated objectives of the policy were to target black money, reduce corruption, and remove fake currency notes. In the service of these objectives, the government placed deposit limits on customers who did not comply with "Know Your Customer" norms and set a deadline of December 31, 2016 for the return

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[2]Lagos and Zhang (2018) argue theoretically that monetary models without money are generically poor approximations even to highly developed credit economies.

[3]Alvarez and Lippi (2009) examine the impact of financial innovation on the demand for cash.

Figure 1: Large Denomination Legal Tender
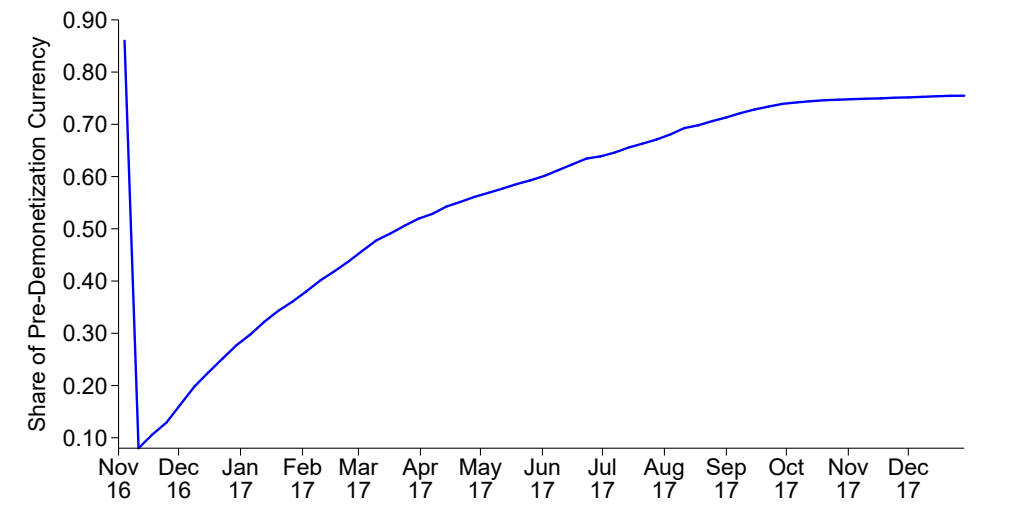
Notes: The figure plots the value of old 500 and 1000 notes (before November 8, 2016) and new 500 and 2000 notes (after November 8, 2016) as a share of total currency in circulation on November 4, 2016 using the currency chest data described below.

of old notes.[4]

Figure 3 shows the path of large legal tender denomination notes as a share of total pre-announcement currency outstanding, using the currency chest data described below. The old 500 and 1000 notes accounted for 86% of pre-demonetization currency. To maintain secrecy prior to the policy's announcement, the government did not print and distribute a large quantity of new notes. Printing press constraints then prevented the government from quickly replacing more than a fraction of this total with new notes. Thus, total currency declined overnight by 75% and recovered only slowly over the next several months.

While the slow replacement of notes led to a decline in currency, it did not affect the overall size of the RBI's balance sheet or market interest rates. The immediate consequence was to increase deposits at commercial banks as households deposited old notes but could not freely withdraw new notes due to the cash shortage.[5] The RBI initially required banks

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[4]The December 31st limit applied to ordinary note holders. Non-resident Indian citizens could continue to deposit old notes until June 30, 2017. Customers who did not comply with the KYC norms could deposit a maximum of Rs 50,000. While all commercial banks and urban cooperative banks were allowed to accept deposits in old currencies, district cooperative banks (DCCBs) were prohibited to do so.

[5]As we later show, the supply of new notes in a geographic area determined the total amount of withdrawals by households in that area. There were also legal limitations on withdrawals from individual accounts. The exchange of old for new notes was initially restricted to Rs 4000 ($60) per person per day, cash withdrawals from bank accounts were initially limited to Rs. 10,000 ($150) per day and Rs 20,000 ($300) per week, and withdrawals from ATM machines were initially restricted to Rs 2000 ($30) per day per card. These

to hold these deposits as reserves at the RBI by increasing the cash reserve ratio to 100% on all incremental deposits received between September 16 and November 11. Since these reserves paid no interest while banks continued to pay positive interest on their deposits, on December 6 the RBI withdrew the increase in the reserve ratio and instead absorbed the deposits by issuing short-term Market Stabilization Bonds (MSB).[6] Figure 2 shows the overall stability of RBI liabilities and the initial increase in commercial bank deposits, later replaced by MSB issuance.[7] The stability of total liabilities also reflects the near total restoration of demonetized notes to the RBI, contrary to expectations early on that the inability to deposit black money would lead to the liquidation of a portion of the RBI's currency liabilities.[8] Thus, demonetization amounted to a forced conversion of household and business assets from cash into bank deposits and a corresponding exchange of currency for obligations to commercial banks on the liabilities side of the RBI's balance sheet.

Figure 3 plots a number of policy and market interest rates around demonetization. Not only did demonetization not coincide with any changes in the official policy rates (repo and reverse repo) used by the RBI, but private rates also changed little. While households were forced to deposit cash into banks, they could freely access these funds in the form of cheques, debit cards or credit cards. The only restriction was on spending using cash. This is the sense in which the Indian demonetization episode speaks directly to the importance of cash. In cashless-limit Keynesian models, monetary policy impacts the economy through a change in interest rates. In the case of the Indian demonetization there was no change in market interest rates but a swap between two forms of RBI liabilities.

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limits were progressively relaxed and finally removed on January 30, 2017. The RBI carved out exceptions for special circumstances such as weddings. In addition it was announced that demonetized notes could be used to pay for certain transactions such as utility bills or to buy airline or train tickets. In total, there were 21 separate press releases specifying rules changes issued by the RBI in November alone. Banerjee, Breza, Chandrasekhar, and Golub (2018) document general confusion about deposit and withdrawal limits caused by these many rules changes. Our focus in this paper concerns the total cash available for withdrawal and not how account limits affected the distribution of withdrawals across households.

[6]MSBs are interest-paying government bonds sold by the RBI specifically to absorb liquidity and take the form of reverse-repo transactions. Technically, the RBI raised the ceiling on the quantity of MSB transactions it would conduct. In the peak months of demonetization (November and December 2016) the bonds took the form of 'cash management bills' with maturities of between 14 and 42 days.

[7]The currency liabilities shown in figure 2 decline more gradually than the sharp drop in legal tender shown in figure 3. The difference occurs because demonetized notes remained liabilities of the RBI until they were exchanged for deposits or new notes or the time window to return them closed.

[8]According to RBI (2018), 99% of total 500 and 1000 notes in circulation prior to demonetization were returned to the RBI.
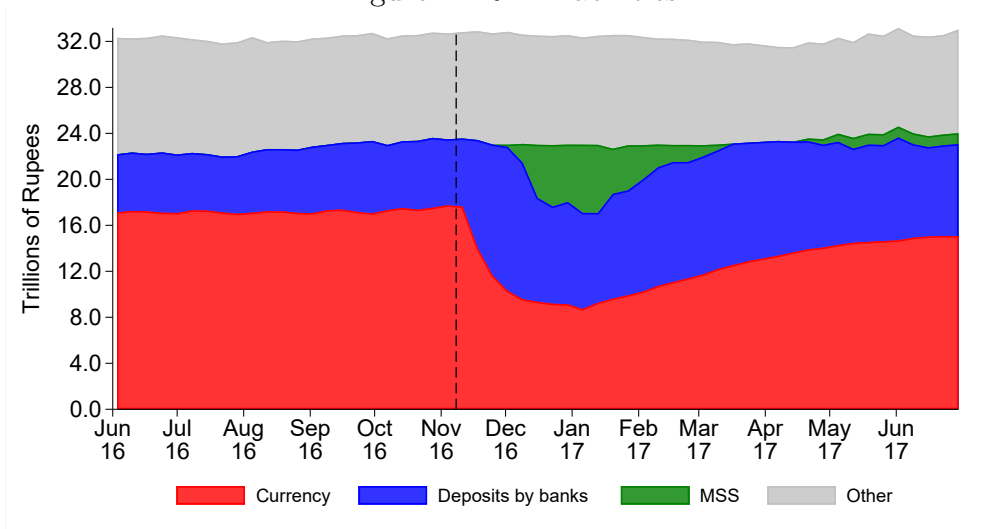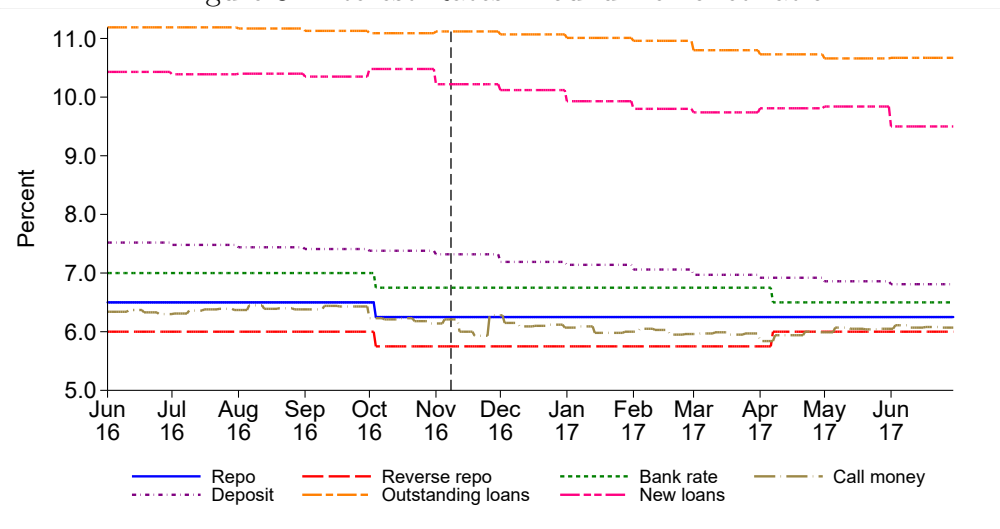
Figure 2: RBI Liabilities

Figure 3: Interest Rates Around Demonetization

3   Model

In this section we present a model of demonetization. The goal is to generate testable implications that we then take to the data. The model is a closed economy comprised of a continuum of identically sized regions indexed by i. The agents are households, firms,

banks, and the government. Each region produces a non-traded good and a unique variety of a good ω which is traded freely across regions. We will consider both the extremes of perfect labor mobility and perfectly immobile labor. An important friction in the labor market is downward nominal wage rigidity as in Schmitt-Grohé and Uribe (2016) and owing to which equilibrium employment can fall short of inelastically supplied labor and give rise to involuntary unemployment. This assumption is consistent with the evidence in Kaur, Supreet (forthcoming) for wages in India.

3.1 Households

Households consume traded and non-traded goods and there are two stores of value, cash, M and interest earning deposits, D. The demand for cash arises for two reasons: Firstly, because of a cash-in-advance (CIA) constraint, along the lines of Lucas (1982), Lucas and Stokey (1987), and Svensson (1985). Secondly, because of a tax advantage whereby holding cash facilitates tax evasion and reduces the effective tax rate households pay. Households in each region i supply $\bar{N}$ units of labor inelastically. They choose consumption of tradeables $C_{i,t}^T$, consumption of nontradeables $C_{i,t}^N$, bank deposits $D_{i,t}$, and cash holdings to carry into the next period $M_{i,t}$ to solve:

$$\max_{C_{i,t}^T, C_{i,t}^N, D_{i,t}, M_{i,t}} \sum_{t=0}^{\infty} \beta^t U(C_{i,t})$$

subject to,

$$P_{i,t}C_{i,t} + D_{i,t} + M_{i,t} \leq R_{t-1}D_{i,t-1} + M_{i,t-1} + (1-\tau(\eta_{i,t}))W_{i,t}N_{i,t} + T_{i,t}, \tag{1}$$

$$\kappa P_{i,t}C_{i,t} \leq M_{i,t-1} + T_{i,t}^M, \tag{2}$$

$$C_{i,t} = (C_{i,t}^T)^\alpha (C_{i,t}^N)^{1-\alpha}, \tag{3}$$

where all variables except for C and labor N are nominal and denominated in the unit of account (rupees).[9] In the budget constraint (1), $\eta_{i,t} = \frac{M_{i,t}}{W_{i,t}N_{i,t}}$ is the ratio of cash balances accumulated in period t to labor income, where $W_{i,t}$ denotes the wage, $\tau(\eta_{i,t})$ is the effective labor income tax rate with $-1 < \tau'(\eta_{i,t}) < 0$ so that the tax rate is decreasing in the ratio of cash holdings relative to labor income, and $T_{i,t}$ contains all transfers received from the government (cash and non-cash) and from firms and banks that are owned by households.

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[9]We exclude the expectations operator in the objective function because we only consider a perfect foresight shock, consistent with the demonetization experiment.

Equation (2) gives the CIA constraint wherein a fraction $0 < \kappa \leq 1$ of consumption spending requires a cash payment. This cash payment can be made using any money holdings brought into period t from $t-1$, $M_{i,t-1}$, and cash transfers $T_{i,t}^M$ received from the government at time t. Total consumption is an aggregate of traded and non-traded consumption, with the traded good itself an aggregate of varieties from different regions: $C_{i,t}^T = \left(\int_0^1 C_{i,t}^T(\omega)^{\frac{\sigma-1}{\sigma}} d\omega \right)^{\frac{\sigma}{\sigma-1}}$, where ω is the unique variety of tradable good produced by firms in region i. The price aggregators are $P_{i,t} = (\alpha^\alpha (1-\alpha)^{1-\alpha})^{-1} (P_t^T)^\alpha (P_{i,t}^N)^{1-\alpha}$, and $P_t^T = \left(\int_0^1 P_t^T(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}$.

The first order conditions are given by:

$$C_{i,t}: \qquad U'(C_{i,t}) = (\lambda_{i,t} + \kappa \theta_{i,t}) P_{i,t}, \qquad (4)$$

$$M_{i,t}: \qquad \lambda_{i,t} (1 + \tau'(\eta_{i,t})) = \beta [\lambda_{it+1} + \theta_{it+1}], \qquad (5)$$

$$D_{i,t}: \qquad \lambda_{i,t} = \beta R_t \lambda_{it+1}, \qquad (6)$$

$$C_{i,t}^N: \qquad P_{i,t}^N C_{i,t}^N = (1-\alpha) P_{i,t} C_{i,t} \qquad (7)$$

$$C_{i,t}^T: \qquad P_t^T C_{i,t}^T = \alpha P_{i,t} C_{i,t} \qquad (8)$$

$$C_{i,t}^T(\omega): \qquad C_{i,t}^T(\omega) = \left(\frac{P_t^T(\omega)}{P_t^T} \right)^{-\sigma} C_{i,t}^T \qquad (9)$$

along with the complementary slackness condition,

$$\theta_{i,t} \cdot (\kappa P_{i,t} C_{i,t} - M_{it-1} - T_{i,t}^M) = 0 \qquad (10)$$

where $\lambda_{i,t}$ is the Lagrange multiplier on the budget constraint and $\theta_{i,t}$ is the Lagrange multiplier on the CIA constraint. We will use the functional form $\tau(\eta_{i,t}) = \frac{\bar{\tau}}{e^{\nu \eta_{i,t}}}$ where $0 < \nu < 1$.

In an interior equilibrium for M and D,

$$\left(1 + \frac{\theta_{i,t+1}}{\lambda_{i,t+1}} \right) \frac{1}{(1 + \tau'(\eta_{i,t}))} = R_t.$$

As is evident, even if the gross interest rate $R_t > 1$ the CIA constraint does not need to bind ($\theta = 0$), because households will choose to hold money because of the tax advantage $\tau'(\eta_{i,t}) < 0$.

3.2 Banks

Banks take in deposits and lend to firms and to the government. Banks are perfectly competitive and both kinds of loans are perfect substitutes and earn interest R_t. Market clearing

requires

$$\int_i A_{i,t}^f di + A_t^g = \int_i D_{i,t} di,$$

where $A_{i,t}^f$ is lending to firms and A_t^g is lending to the government.

3.3 Firms

Firms in both the tradable and non-tradable sectors are perfectly competitive. Each firm faces a working capital constraint where a fraction φ of the wage bill needs to be paid in advance. Firms take a loan $B_{i,t}^f = \varphi W_{i,t} N_{i,t}$ from the bank for this purpose. The production function for either good is $Y_t = N_t$. With perfect competition price equals marginal cost:

$$P_t^T(\omega) = P_{i,t}^N = (1 + \varphi(R_t - 1))W_{i,t}.$$

For now we have indexed the wage rate by i to allow for immobile labor.

3.4 Downward Wage Rigidity

As in Schmitt-Grohé and Uribe (2016) the main friction is that nominal wages are downwardly rigid by a factor $0 < \gamma \leq 1$,

$$W_{i,t} \geq \gamma W_{it-1}, \tag{11}$$

which can prevent full employment. If $\gamma = 1$ then nominal wages can never fall. The evidence in Kaur, Supreet (forthcoming) implies $\gamma = 1$. When the constraint does not bind, $N_{i,t} = \bar{N}$. Consequently we have the complementary slackness condition,

$$(\bar{N} - N_{i,t})(W_{i,t} - \gamma W_{it-1}) = 0$$

when labor is immobile across regions, and

$$(\bar{N} - N_t)(W_t - \gamma W_{t-1}) = 0$$

when labor is perfectly mobile.

3.5 Government

The consolidated budget constraint of the government satisfies,

$$\int_0^1 \left(M_{i,t}^s + B_{i,t}^g + \tau(\eta_{i,t}) W_{i,t} N_{i,t} \right) di = \int_0^1 \left(T_{i,t}^M + T_{i,t}^g + M_{i,t-1}^s + R_{t-1} B_{i,t-1}^g \right) di$$

$$T_{i,t}^M = M_{i,t}^s - M_{i,t-1}^s \qquad \forall i \in [0,1],$$

where $B_{i,t}^g$ denotes government bonds issued in period t. The government raises funds through money creation, debt issuance, and labor income taxes, all of which is transferred to households.

3.6 Market Clearing

Traded goods markets clear countrywide, $\int_i C_{i,t}^T(\omega) di = Y_t^T(\omega)$. Non-traded goods markets clear by region, $C_{i,t}^N = Y_{i,t}^N$. Further, $A_{i,t}^f = B_{i,t}^f$, $A_t^g = B_t^g$ and $M_{i,t}^s = M_{i,t}$. $\bar{M}_{i,t}^s$ is the cash that is supplied to region i.

3.7 Pre-Demonetization Steady State

The economy in period -1 is in a steady state where because of tax evasion incentives the CIA does not bind, $M_{-1} > \kappa P_{-1} C_{-1}$. This requires that $\kappa(1 + \varphi(\frac{1}{\beta} - 1)) < \frac{1}{\nu} \ln\left(\frac{\nu\bar{\tau}}{1-\beta}\right)$, that is, that the tax rate $\bar{\tau}$ is sufficiently high relative to the interest rate and to the fraction of spending that needs to be undertaken in cash κ. This assumption reflects the argument made by the Indian government that an important fraction of pre-demonetization cash was 'black money' held for tax evasion purposes.

Proposition 1 *Pre-demonetization steady state*
In period -1 all regions are in a symmetric zero inflation steady state with $M^s = M_{-1}$, and

1. *The economy is in full employment:*

$$N_{-1} = \bar{N}, \qquad Y_{-1}^T = N_{-1}^T = \alpha\bar{N}, \quad Y_{-1}^N = N_{-1}^N = (1-\alpha)\bar{N}. \tag{12}$$

2. *Real money balances are increasing in the level of consumption C and in the labor*

income tax $\bar{\tau}$ and decreasing in the interest rate $R_{-1} = 1/\beta$:

$$\frac{M_{-1}}{P_{-1}} = \frac{\eta_{-1} C_{-1}}{(1 + \varphi(R_{-1} - 1))}, \qquad \eta_{-1} = \frac{1}{\nu} \ln\left(\frac{\nu\bar{\tau}}{1 - (1/R_{-1})}\right). \tag{13}$$

3. Nominal wages and prices are given by:

$$W_{-1} = \frac{M_{-1}}{\bar{N}\eta_{-1}}, \quad P_{-1}^T = P_{-1}^N = (1 + \varphi(\beta^{-1} - 1))\frac{M_{-1}}{\bar{N}\eta_{-1}}. \tag{14}$$

∎

With a constant level of money supply in the economy, the wage friction does not bind and the economy is in full employment with a fraction α of labor employed in the traded sector and $(1 - \alpha)$ in the non-traded sector.

3.8   Demonetization

At the start of period 0 the government (unexpectedly) announces that only a fraction of cash which households carry into period 0 is legal tender and can be used for transaction purposes (demonetization) and requires the remaining cash be deposited at the pre-fixed interest rate of R_{-1}. This policy corresponds to a drop in available money balances in period 0, forcing households off their deposit Euler equation (6). At the start of period 1 demonetization ends and the money supply returns to the level required to maintain full employment. There is no uncertainty following the announcement of the demonetization shock so household decisions at the end of period 0 reflect the anticipated cash infusion.

We first describe the solution for the case when the demonetization is uniform across all regions in 0. The solution remains symmetric and the path of cash is such that the CIA and wage constraints bind in period 0 before becoming loose again in period 1 and after.[10]

Proposition 2 *Uniform demonetization*
Let $Z = M_0^s/M_{-1}^s = M_0/M_{-1}$ where $0 < Z < 1$ so that the CIA binds and the wage constraint

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[10]As long as the CIA binds we can solve for the outcomes in period 0 without the solutions for period 1 and beyond. This is because interest rates are pre-fixed at R_{-1} and the deposit Euler equation and money Euler equations are irrelevant. To verify the conditions under which the CIA binds we need to solve fully for the dynamic solution. We provide the full solution in the appendix. Due to one-sided wage rigidity, there are multiple values for M in period 1 which guarantee full employment and we choose the minimal such value. This value requires an equilibrium wage $W_1 > \gamma W_0 = \gamma^2 W_{-1}$ at which the downward wage rigidity is not binding. If $\gamma \approx 1$ then $M_1 \approx M_{-1}$ and the cash to GDP ratio returns to the pre-demonetization level.

binds, that is $\kappa P_0 C_0 = M_0$ and $W_0 = \gamma W_{-1}$. If Z is sufficiently low relative to the downward rigidity of wages,[11] *$Z \cdot \frac{\eta_{-1}}{\kappa(1+\varphi(\beta^{-1}-1))} < \gamma$, then:*

1. *Output and employment declines:*

$$Y_0^T = N_0^T = \frac{Z}{\gamma} \cdot \frac{\eta_{-1}}{\kappa(1+\varphi(\beta^{-1}-1))} \cdot \alpha \bar{N},$$

$$Y_0^N = N_0^N = \frac{Z}{\gamma} \cdot \frac{\eta_{-1}}{\kappa(1+\varphi(\beta^{-1}-1))} \cdot (1-\alpha)\bar{N},$$

$$\frac{Y_0}{Y_{-1}} = \frac{Z}{\gamma} \cdot \frac{\eta_{-1}}{\kappa(1+\varphi(\beta^{-1}-1))}. \tag{15}$$

2. *Lending by banks to firms decline:*

$$\frac{B_0^f}{P_0} = \frac{\varphi N_0}{(1+\varphi(R_{-1}-1))} < \frac{B_{-1}^f}{P_{-1}}. \tag{16}$$

3. *Nominal wages and prices are given by:*

$$W_0 = \gamma W_{-1}, \quad P_0^T = P_0^N = (1+\varphi(\beta^{-1}-1))\gamma W_{-1}. \tag{17}$$

∎

The solution for output features a proportional decline between output and Z. This proportionality arises because of the binding CIA constraint $M_0 = \kappa P_0 C_0$ which tightly links cash in period 0 to output $Y_0 = C_0$.[12] We also have that the ratio of money holdings to labor income falls $\eta_0 < \eta_{-1}$ owing to which the effective tax rate rises $\tau_0 > \tau_1$, but this is not distortionary because of perfectly inelastic labor supply. The shadow interest rate, which is the interest rate consistent with the deposit Euler equation, rises: $R_0^s \equiv \frac{\lambda_0}{\beta \lambda_1} = \frac{1}{(1-\nu\tau(\eta_0))} > \frac{1}{(1-\nu\tau(\eta_{-1}))} = R_{-1}$.

We next consider the case where the decline in M is not uniform across regions, as we will exploit in our empirical work. The government reduces the supply of cash in region i in

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[11] Recall that for the CIA not to bind in period -1 we require that $\frac{\eta_{-1}}{\kappa(1+\varphi(\beta^{-1}-1))} > 1$ which means that we need $\frac{Z}{\gamma}$ to be sufficiently lower than 1 to compensate for this. The reason it does not depend only on Z/γ is because the nominal wage when the CIA binds is different from when the CIA does not bind.

[12] To see this, start from the binding CIA constraint $M_0 = \kappa P_0 C_0$ and substitute the equilibirium conditions $P_0 = (1+\varphi(R_{-1}-1))W_0 = (1+\varphi(\beta^{-1}-1))\gamma W_{-1}$ and $Y_t = C_t = N_t$ and the definitions $\eta_{-1} = M_{-1}/(W_{-1}N_{-1})$ and $Z = M_0/M_{-1}$ to arrive at equation (15) in the proposition. As should be clear, while in our setup P_0 is sticky downwards because of the downward wage rigidity, any nominal friction which keeps P_0 from falling will result in a similar expression.

a proportion $Z_i \in (0,1)$, i.e. $M_{i,0}^s = Z_i M_{-1}^s$ such that $Z_i = Z(1 + \epsilon_i)$ and where $\int_i \epsilon_i di = 0$. We assume households cannot undo the heterogeneous distribution of cash across regions through financial markets.

Proposition 3 *Non-uniform demonetization*

If the drop in each region is sufficient to make the CIA constraint and wage constraint bind in all regions, that is, $\kappa P_{i,0} C_{i,0} = M_{i,0}$ and $W_{i,0} = \gamma W_{-1}$ $\forall i$, then:

1. *Regions with higher Z_i have smaller declines in output. The differential is increasing in the size of the non-traded sector:*

$$\frac{Y_{i,0}}{Y_{i,-1}} = \frac{Y_0^T(\omega) + Y_{i,0}^N}{Y_{i,-1}} = \frac{\alpha Z + (1-\alpha)Z_i}{\gamma} \cdot \frac{\eta_{-1}}{\kappa(1 + \varphi(\beta^{-1} - 1))}. \tag{18}$$

2. *Borrowing by firms falls by less in regions with higher Z_i:*

$$\frac{B_{i,0}^f}{P_0} = \frac{\varphi Y_{i0}}{(1 + \varphi(\beta^{-1} - 1))}. \tag{19}$$

3. *Nominal wages and prices are given by:*

$$W_{i,0} = \gamma W_{-1}, \quad P_0^T = P_{i,0}^N = (1 + \varphi(\beta^{-1} - 1))\gamma W_{-1}. \tag{20}$$

∎

The impact of the idiosyncratic component of the money shock is decreasing in the size of the traded sector. As $\alpha \to 1$ there is no cross-regional variation in output. Regional employment tracks regional output and, because of downward wage rigidity, the wage is equalized across regions regardless of whether there is labor mobility. Bank credit growth, $B_{i,t}^f/P_0$, is increasing in Z_i. If all banks are national banks and market clearing is given by $\int_i A_{i,t}^f di + A_t^g = \int_i D_{i,t} di$ then there is no necessary relation between local demand for loans and loans extended by banks. If however banks have a location bias then there is differential loan growth. Alternatively, a vanishingly small cost to firms that borrow from banks outside their regions (or of banks that lend outside their region of location), given that interest rates are the same, would generate a greater decline in credit creation by banks located in a region with a smaller Z_i.

3.9 Endogenous κ

We now extend the model in one important dimension: we allow households to endogenously change κ by investing in a 'finance' technology $f_{i,t}$ to lower their dependence on cash transactions. This investment encompasses a broad range of actions that households can undertake including switching to alternative payment methods like debit cards, credit cards, and e-wallets and convincing retailers to open an informal line of credit or to accept old notes. The endogenous κ will allow the model to better match our empirical results by breaking the unit elasticity between M and output in equation (15).

Specifically, $\kappa(f_{i,t})$ is such that $\kappa'(f_{i,t}) < 0, \kappa(0) = \bar{\kappa}$. Making this investment entails a utility loss $h(f_{i,t})$ such that $h'(f_{i,t}) > 0, h''(f_{i,t}) \geq 0, h(0) = 0$. The household's objective function is now given by,

$$\max_{C_{i,t}^T, C_{i,t}^N, D_{i,t}, M_{i,t}, f_{i,t}} \sum_{t=0}^{\infty} \beta^t \left[U(C_{i,t}) - h(f_{i,t}) \right]$$

and the CIA constraint takes the form,

$$\kappa(f_{i,t}) P_{i,t} C_{i,t} \leq M_{i,t-1} + T_{i,t}^M. \tag{21}$$

The budget constraint remains unchanged. In addition to the F.O.C listed previously (4-9) (where κ is now an endogenous variable) we have the condition,

$$h'(f_{i,t}) = -\theta_{i,t} \kappa'(f_{i,t}) P_{i,t} C_{i,t}$$

according to which households will invest in the finance technology if the CIA constraint binds and not otherwise. It follows that households do not invest in the finance technology in periods -1 and 1 and in these periods $\kappa = \bar{\kappa}$ while they do invest in the period of demonetization.

The full solution requires solving for $\theta_{i,0}, f_{i,0}, \eta_{i,0}$ using the following three equations.

$$\theta_{i,0} = \frac{1}{Z_i M_{-1}} - \frac{1}{\kappa(f_{i,0})} \frac{\beta \lambda_{i,1}}{1 + \tau'(\eta_{i,0})}$$

$$\eta_{i,0} = \frac{Z_i(1 + \varphi(\beta^{-1} - 1))}{\alpha \mathcal{I} + (1 - \alpha) \frac{Z_i}{\kappa(f_{i,0})}}$$

$$\theta_{i,0} Z_i M_{-1} = -\frac{h'(f_{i,0}) \kappa(f_{i,0})}{\kappa'(f_{i,0})}$$

15

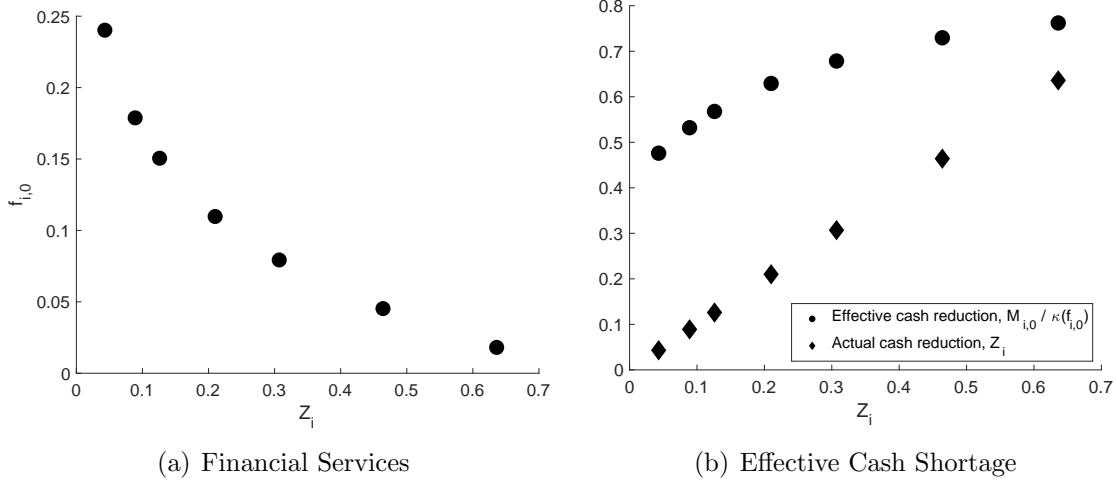(a) Financial Services (b) Effective Cash Shortage

Figure 4: Adoption of non-cash forms of payment

where $\lambda_{i,1} = \frac{\eta_{-1}}{M_1(1+\varphi(1/\beta-1))}$ and $\mathcal{I} = \int \frac{Z_j}{\kappa(f_{j,0})}dj$. In the absence of a closed form solution, we provide a numerical illustration of how $f_{i,0}$ varies with Z_i (see the appendix for details). Figure 4(a) shows that regions with a smaller drop in cash (higher Z) invest less in financial services (f). Because of this adoption of financial services the effective cash shortage is smaller relative to the measured cash shortage in each region. In addition, because of the selection effect there is less heterogeneity in the effective cash shortage across regions, i.e. $Z_i/\kappa_{i,0}$ is much less dispersed that the measured cash shortage Z_i as depicted in Figure 4(b). Overall, the cross-sectional relationship between cash and output is attenuated.

To summarize, the following predictions follow from this section: Districts experiencing more severe demonetization will have: 1) Relative reductions in employment and output. 2) Faster adoption of alternative payment technologies. 3) Lower bank credit growth, and 4) Cross-sectional estimates provide a lower bound for aggregate effects. In the next sections we empirically examine the testable predictions of the model and provide a lower bound estimate for the aggregate impact of demonetization.

Table 1: Data Sets

Name	Source	Coverage
Currency chests	RBI	Daily cash flow accounting statements by note denomination for all currency chests in India aggregated to district level
Consumer Pyramids	Centre for Monitoring the Indian Economy (CMIE)	Monthly household survey containing employment status of about 110,000 adults in sample
Nightlights	VIIRS DNB	Low-light imaging data collected by satellite and filtered to measure the quantity of artificial (i.e. human-generated) light in an area
ATM transactions	National Payments Corporation of India (NPCI)	Monthly value of all ATM withdrawals covered by NPCI aggregated to district level
POS transactions	National Payments Corporation of India (NPCI)	Monthly value of all point-of-sale (POS) transactions covered by NPCI aggregated to district level
e-Wallet transactions	Wallet company	Monthly index of value of e-wallet transactions aggregated to district level
Bank deposits	RBI	End-of-quarter deposits at all bank branches in each district
Bank credit	RBI	End-of-quarter credit outstanding from all bank branches in each district
District GDP	Indicus	Annual district GDP per capita and sectoral GDP shares through 2015

4 Data and Summary Statistics

4.1 Data

We merge several data sets, many of which have not previously been used in academic research. The variety of data sets allow us to report both financial and real outcomes including coverage of the informal sector. Our main geographic level of aggregation is the district. India contains approximately 600 districts which partition the country. Table 1 summarizes the data sets used.

Currency shocks. We construct geographic demonetization shocks using currency chest records maintained by the RBI. A currency chest functions as a warehouse of currency notes for the RBI but is physically located in and administered by a commercial bank. There are approximately 4000 chests spread across the country. A chest may receive newly printed

Table 2: Example Currency Chest

Date	Note		Inflows			Outflows			
		Open	*Remit*	*DI*	*Dep*	*Soiled*	*DO*	*Wit*	*Close*
11/15/2016	2000	100	50	20	0	0	10	80	80
11/15/2016	1000	800	0	0	200	600	0	0	400
11/15/2016	500	400	10	0	20	100	0	10	320

notes either directly from one of the 19 RBI issue offices or from one of approximately 600 "hub" chests. Each chest in turn sends currency to and receives currency from individual commercial banks located in its geographic vicinity. Thus, all newly printed notes available for withdrawal from a commercial bank first pass through the correspondent currency chest.

Our data consist of daily cash flow accounting statements reported by each currency chest, separately by note denomination. Table 2 provides an example for a hypothetical chest after demonetization has occurred. The statements report the opening quantity of notes at the chest (*Open*), new notes remitted directly by an RBI office (*Remittances*), notes received from other chests (*DI*), deposits of notes by commercial banks (*Dep*), soiled notes sent back to an RBI office for destruction (*Soiled*), notes sent to other chests (*DO*), withdrawals of notes by commercial banks (*Wit*), and the closing quantity of notes at the chest (*Close*). We aggregate the chest-level data to the district level.

We use the chest data to construct measures of the quantity of demonetized and new notes in a geographic area at any point in time. We define the currency replacement rate in district i at date t post-demonetization as the net value of new 2000 and 500 notes received by currency chests in the district as of date t divided by the total value of demonetized 1000

and 500 notes. We operationalize this measure as follows:

$$\text{New 2000 notes:} \qquad M_{i,t}^{2000} = \sum_{s=\text{Oct 26, 2016}}^{t} \left(Remit_{i,s}^{2000} + ND_{i,s}^{2000} \right), \qquad (22)$$

$$\text{New 500 notes:} \qquad M_{i,t}^{500,new} = \sum_{s=\text{Nov 9, 2016}}^{t} \left(Remit_{i,s}^{500} + ND_{i,s}^{500} \right), \qquad (23)$$

$$\text{Demon. 1000 notes:} \qquad M_{i}^{1000} = \sum_{s=\text{Nov 9, 2016}}^{\text{Jan 31, 2018}} Soiled_{i,s}^{1000} + Close_{i,\text{Jan 31, 2016}}^{1000} \qquad (24)$$

$$\text{Demon. 500 notes:} \qquad M_{i}^{500,old} = \sum_{s=\text{Nov 9, 2016}}^{\text{Dec 31, 2017}} Soiled_{i,s}^{500}, \qquad (25)$$

where $ND_{i,s} = DI_{i,s} - DO_{i,s}$ denotes net diversions of currency received from other chests. We measure new 2000 notes by summing notes received directly from RBI offices and net notes received from other chests.[13] We measure new 500 notes, $M_{i,t}^{500,new}$, analogously. We measure demonetized 1000 notes, M_{i}^{1000}, as the sum from the day after demonetization to the last day in our data set, January 31, 2018, of the value of 1000 notes returned to RBI offices plus any 1000 notes remaining in a chest as of that date. Finally, we measure demonetized 500 notes, $M_{i}^{500,old}$, by summing the value of 500 notes returned to RBI offices.[14] The measures of demonetized notes do not have t subscripts because they capture the stock of notes in chests or in circulation as of November 8. With these definitions, we can define the demonetization shock $Z_{i,t}$ as the ratio of new 2000 and 500 notes to demonetized 1000 and

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[13]This measure spikes temporarily when a chest receives notes from an RBI issue office which it subsequently sends to other chests. To remove these spikes, we additionally apply a lower-envelope operator to $M_{i,t}^{2000}$ which takes the minimum value of new notes over periods t forward. That is, our actual measure modifies equation (22) to be $M_{i,t}^{2000} = \min_{t' \geq t} \sum_{s=\text{Oct 26, 2016}}^{t'} \left(Remit_{i,s}^{2000} + ND_{i,s}^{2000} \right)$. We do not apply this operator to 500 notes as defined in equation (23) because the data do not distinguish between net diversions of new and demonetized 500 notes. Our results are quantitatively robust to not applying this operator to the 2000 notes.

[14]We cannot include the January 31, 2018 balance of old 500 notes in the measure of $M_{i}^{500,old}$ because the data do not distinguish between balances of old and new 500 notes. Likewise, soiled 500 notes returned after demonetization may contain some new 500 notes, explaining why we truncate the summation at the end of December 2017. While these factors imply $M_{i}^{500,old}$ is measured with error, we believe such measurement error is small. Moreover, the vast majority of cross-sectional variation in currency replacement comes from 1000 and 2000 notes, not 500 notes. A regression of $\ln Z_{i,t}$ on $\ln(M_{i,t}^{2000}/M_{i}^{1000})$ for $t =$ December 2016 yields a coefficient of 0.82 and an R^2 of 0.85. Adding $\ln(M_{i,t}^{500,new}/M_{i,t}^{500,old})$ to the regression yields a statistically highly significant coefficient of 0.10 on the new variable but raises the R^2 only slightly to 0.89.

500 notes:

$$Z_{i,t} = \frac{M_{i,t}^{2000} + M_{i,t}^{500,new}}{M_i^{1000} + M_i^{500,old}}. \tag{26}$$

To remove districts with implausible replacement rates, we drop observations with $Z_{i,t} <$ 0, $M_i^{500,old} \leq 0$, or where $\sum_{s=\text{Nov 9, 2016}}^{t} \left(Withdrawals_{i,s}^{2000} - Deposits_{i,s}^{2000} \right) < 0$ or differs from $M_{i,t}^{2000}$ by more than a factor of 3. That is, we require that new currency arriving in a district be non-negative, that we observe a positive quantity of old 500 notes, that cumulative deposits of 2000 notes by commercial banks not exceed cumulative withdrawals, and that cumulative withdrawals net of deposits (i.e. net new 2000 notes actually received by commercial banks) not differ from arrivals of new 2000 notes by too much.[15] Applying these criteria removes 47 of 591 districts which collectively contain less than 3% of demonetized currency.

Employment. We obtain data on employment status from Consumer Pyramids for the period January 2016 to October 2017. Unlike countries such as the United States, India does not have a governmental monthly household survey or a monthly survey of establishments.[16] The Centre for Monitoring the Indian Economy, a private organization, conducts a nationally representative household survey referred to as Consumer Pyramids, which includes questions on employment status similar to those asked in the Current Population Survey (CPS) in the United States. Specifically, an individual counts as employed if on the day of the survey or the day prior, the individual (i) did any paid work, (ii) was on paid or unpaid leave, (iii) was not working because his/her workplace was temporarily shut down for maintenance or labor dispute but expected to resume work within 15 days, (iv) owned a business in operation, or (v) assisted in a family business. The survey covers roughly 110,000 adults (persons 15+) per month, comparable to the sample size (although not the coverage rate) of the CPS.[17]

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[15]Cumulative withdrawals net of deposits may differ from new arrivals of notes because currency withdrawn by a commerical bank in one district may go to a customer who re-deposits the notes in a bank in a different district. However, large discrepancies between the measures are rare and signal some restriction on withdrawals which we do not observe.

[16]In April 2018 the Central Statistics Office began reporting monthly employment counts for formal sector firms based on administrative tax records, with data back to September 2017. The non-coverage of the demonetization period or of informal sector employment make these data inappropriate for our analysis.

[17]The survey shares other similarities with the CPS and the Survey of Income and Program Participation (SIPP), such as the use of a stratefied sampling design (based on the 2011 Census) and a rotation structure wherein individual sampling units enter the survey every four months. The survey does not include any units from the following states or union territories: Arunachal Pradesh, Nagaland, Manipur, Mizoram, Tripura, Meghalaya, Sikkim, Andaman & Nicobar Islands, Dadra & Nagar Haveli, Lakshadweep and Daman and Diu.

We construct district-month measures of employment and population by aggregating the individual observations using the survey weights. This step introduces four complications. First, while the survey has national representation, it does not field in every district in every month. Rather, it uses a rotation schedule wherein each primary sampling unit (a town or village) with households in the sample gets visited once every four months. This pattern means that most districts appear in the sample only once every four months, with larger districts surveyed more frequently. The typical month therefore contains observations drawn from roughly 150 districts. For this reason, we pool over adjoining months to increase the sample size. Second, the survey is in the field continuously over the course of a month and we do not know the exact interview date for each respondent. We exclude November 2016 from the analysis since responses in that month mix pre-demonetization and post-demonetization outcomes. Third, the survey weights do not aggregate to estimates of district population which are consistent across months. We therefore use the ratio of total employed to persons 15 and older as our main outcome. Finally, we weight regressions using this variable by the number of individual-level observations in the district to reflect the aggregation step.

Nightlights. Our second measure of real activity following demonetization is the change in nightlight intensity. Nightlight intensity refers to low-light imaging data collected by satellite and filtered to measure the quantity of artificial (i.e. human-generated) light in an area. Such data have been used to augment official measures of output and output growth and to generate estimates for areas or periods where official data are unavailable (Henderson, Storeygard, and Weil, 2012). We use the VIIRS DNB data collected by NOAA using the Suomi National Polar Partnership satellite which was launched in 2011 (Elvidge, Baugh, Zhizhin, Hsu, and Ghosh, 2017). Despite the filtering, some stray light remain in these data. NOAA provide annual composites which contain additional processing to remove such stray light. We follow World Bank (2017) in removing cells (roughly 0.5km^2) for which the annual average of the data differ substantially from the annual composites before aggregating to the district level. The resulting data are monthly frequency and contain substantial seasonality. We seasonally adjust the data in both levels and logs by regressing nightlights on district-specific linear time trends and month categorical variables over the period April 2012 to March 2016, remove the month-specific factors, and then keep the series for each district (unadjusted, adjusted in levels, adjusted in logs) with the smallest variance. This procedure uses only data from before demonetization to perform the seasonal adjustment. Finally, we aggregate the monthly data to quarterly to remove very high frequency volatility, dropping

October 2016 from 2016Q4 so that 2016Q4 is (almost entirely) post-demonetization.

ATM/POS. We obtain monthly data for the period January 2016 to June 2017 on the value of ATM withdrawals and point-of-sale (POS) transactions by PIN code from National Payments Corporation of India (NPCI), an umbrella organization set up by the RBI to operate retail payments systems. A POS terminal is a device which enables payment by credit or debit card over a telephone line or internet connection. We aggregate the data to the district level using a concordance file from the post office. Where a PIN code covers multiple districts, we assign the district based on the location of the main post office in the district.

E-Wallet. We obtain monthly indexes of the total value of e-wallet transactions by district from a wallet company for the period September 2016 to July 2017. E-Wallet technology functions similar to pre-paid cards.[18]

Bank deposits and credit. We obtain publicly available end-of-quarter data on bank deposits and credit outstanding by district from the RBI Quarterly Statistics on Deposits and Credit of Scheduled Commercial Banks. These data come from branch-level reporting. Therefore, district-level deposits correspond to deposits in accounts opened at branches within the district. Likewise, district-level credit means loans granted by loan officers at branches within the district regardless of the location of the borrower.

GDP and population. We obtain district-level measures of GDP, sectoral GDP, and population from Indicus, a private data firm, and use these data to convert various series to a per capita basis and as control variables below. We use data from 2015, the last year of data available, in our analysis. We obtain national quarterly seasonally-adjusted nominal and real GDP from OECD.[19]

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[18]The wallet company issued the following disclaimer:"Wallet company shared only normalized data on payments to merchants at an aggregate level for academic research. No user data has been shared in any form. Wallet company does not have any role in drawing inferences of the study and the views expressed in the study are solely of the authors."

[19]The Indian Ministry of Statistics does not publish a seasonally-adjusted measure of quarterly GDP. The OECD series closely mirrors that obtained by applying Census X12 to the unadjusted data.

4.2   Summary Statistics

Table 3 reports cross-district summary statistics for December 2016, March 2017, and June 2017. The median district in December 2016 had received new notes equal to just 31% of its demonetized notes. Essentially all districts experienced a contraction, with the 90th percentile district experiencing a 36% decline in large denomination notes. At the other extreme, the 10th percentile district had only 13% of its large denomination notes replaced. By March 2017, the median replacement rate had risen to 77% and by June 2017 the median district had no net contraction remaining in large denomination currency. Thus, in the first few months demonetization affected essentially all areas of India but with varying intensity, and by summer 2017 the shock had mostly been undone.

4.3   What Determines Geographic Variation in the Shock?

The next section reports cross-sectional correlations of outcome measures with the demonetization shock. Causal interpretation of these correlations requires that the variation in demonetization intensity be uncorrelated with the no-demonetization baseline paths of the outcome variables, similar to the parallel trends assumption required in difference-in-difference estimation. Such a correlation could arise for example if the RBI steered new notes toward areas with secularly growing or shrinking currency demand.

Figure 5 shows a map of the demonetization shock in December 2016 by district, with districts which experienced larger shocks shaded darker. The RBI offices in some states appear to have received more new currency notes than in others, but without a clear geographic pattern across states or across districts within a state. We will address the spatial correlation in what follows by clustering standard errors by state.

The narrative record does not support the supposition that the RBI allocated new notes geographically in a manner determined by local economic conditions, at least for the first few months after demonetization. The official post-partum of the episode contained in the RBI's 2017 annual report (RBI, 2017a, p. 132) starts by acknowledging "the logistical difficulties in supplying banknotes to all currency chests in a short span," suggesting that logistical factors may have played a role in the geographic distribution. It continues: "Fresh notes were distributed to every Issue Office in accordance with a planned allocation. The Regional Office-wise allocation of notes was revised during the last quarter of 2016-17 [calendar quarter 2017Q1] based on the SBNs [demonetized notes] deposited and cash supplied in issue circles during the demonetization period." The RBI has not made public the particulars

Table 3: Summary Statistics

	Mean	Sd	P10	P50	P90	Count
2016m12						
Demonetization shock	0.36	0.24	0.13	0.31	0.64	543
Nightlights (log change)	−0.08	0.22	−0.33	−0.08	0.16	541
ATM transactions (log change)	−0.85	0.42	−1.44	−0.77	−0.42	535
POS transactions (log change)	2.26	0.83	1.35	2.19	3.31	526
E-Wallet transactions (log change)	0.68	0.34	0.34	0.65	1.07	516
Bank deposits (log change)	0.12	0.05	0.06	0.12	0.19	536
Bank credit (log change)	−0.01	0.04	−0.04	−0.01	0.02	536
2015 GDP per capita (Mi)	0.10	0.08	0.04	0.09	0.18	540
2015 Agriculture share of GDP (%)	16.26	12.43	2.70	13.80	34.50	532
2017m3						
Demonetization shock	0.85	0.44	0.39	0.77	1.36	551
Nightlights (log change)	0.18	0.26	−0.09	0.15	0.49	548
ATM transactions (log change)	0.01	0.31	−0.19	0.01	0.24	544
POS transactions (log change)	1.73	0.95	0.87	1.66	2.76	531
E-Wallet transactions (log change)	0.91	0.30	0.54	0.90	1.28	520
Bank deposits (log change)	0.13	0.06	0.07	0.12	0.19	544
Bank credit (log change)	0.06	0.05	0.02	0.07	0.11	544
2015 GDP per capita (Mi)	0.10	0.08	0.04	0.09	0.19	548
2015 Agriculture share of GDP (%)	16.17	12.37	2.70	13.70	34.50	540
2017m6						
Demonetization shock	1.19	0.63	0.52	1.07	1.97	549
Nightlights (log change)	0.28	0.31	−0.02	0.26	0.67	546
ATM transactions (log change)	−0.03	0.21	−0.18	−0.04	0.16	542
POS transactions (log change)	1.77	0.80	0.98	1.69	2.66	530
E-Wallet transactions (log change)	1.14	0.35	0.73	1.16	1.53	518
Bank deposits (log change)	0.12	0.05	0.07	0.12	0.18	542
Bank credit (log change)	0.08	0.06	0.02	0.08	0.12	542
2015 GDP per capita (Mi)	0.10	0.08	0.04	0.09	0.19	546
2015 Agriculture share of GDP (%)	16.17	12.34	2.70	13.70	34.50	538

of the "planned allocation," but its sophistication would have been limited by the secrecy surrounding the policy prior to its announcement as very few officials even within the government knew of the policy ahead of time. Moreover, the RBI in October 2016 could not have known the precise geographic distribution of existing 500 and 1000 notes in circulation. The next sentence of the report indicates that the RBI did not begin to incorporate real-

Figure 5: Demonetization Shock by District
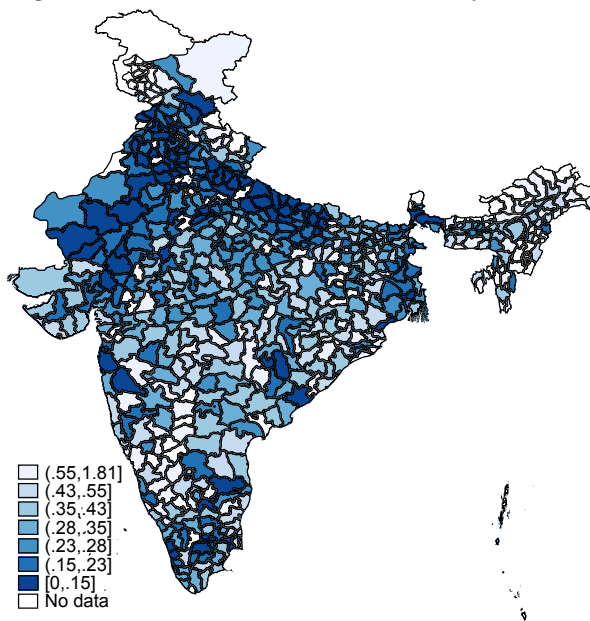
time feedback concerning the geographic distribution of demonetized notes or other currency demand factors until early in 2017. Thus, the narrative record comports with treating the geographic distribution of the demonetization shock as "as good as random" at least through December 2016 and probably afterward as well.

Finally, we look for statistical patterns which would suggest a distribution of new notes in a way correlated with our outcome variables. In the next section, we report figures showing the correlations of outcomes and the demonetization shock before November 2016 and find no evidence of pre-trends in the data. Here we report correlations of the log of $Z_{i,t}$ in December 2016 with other variables in our data set: 2015 GDP per capita, the 2015 share of GDP in agriculture, the distance from the district to the closest RBI office, bank penetration, and pre-demonetization currency per capita. The only variable with a correlation larger than 0.11 in absolute value or statistically significant is the pre-demonetization level of currency per capita – more currency-intensive areas experienced slower replacement rates. This pattern could reflect a desire by the RBI to smooth the per capita allocation of new notes across areas or simply that the RBI did not know the geographic distribution of old notes in real time. There is no reason it would cause a violation of the parallel trends assumption.

Table 4: What is the Currency Shock Correlated With?

	(1)	(2)	(3)	(4)	(5)	(6)
Log GDP per capita	−0.11					0.06
	(0.17)					(0.27)
Agriculture share of GDP		−0.04				−0.11
		(0.08)				(0.10)
Log distance to closest RBI office			0.10			0.03
			(0.06)			(0.07)
Log Bank branches per million persons				−0.11		−0.09
				(0.13)		(0.17)
Log Pre-demonetization currency per capita					−0.27**	−0.28**
					(0.07)	(0.07)
BM df	13.0	9.8	19.7	18.8	19.0	
R^2	0.01	0.00	0.01	0.01	0.07	0.08
Clusters	31	31	33	31	33	31
Observations	538	530	540	535	540	527

Notes: The table reports the correlation coefficient (columns 1-5) and partial correlation coefficient (column 6) with $z_{i,t}$, the log of the currency shock. Standard errors in parentheses clustered by state using the "LZ2" bias-reduction modification suggested by Imbens and Kolesár (2016). The row "BM df" gives the associated t-distribution degrees of freedom for the coefficient. ** denotes significance at the 1 percent level.

5 Empirical Findings

In this section we use the geographic variation in the net drop in cash due to demonetization to document the following results: (i) demonetization caused cash shortages, as evidenced by a sharper decline in ATM withdrawals in areas with larger shocks; (ii) economic activity, as measured by employment rates and nightlights, fell in these areas relative to areas which experienced smaller shocks; (iii) these areas adopted alternative forms of payment; and (iv) deposits increased more and credit fell in these areas. These results, which come from disparate data sources and reflect different aspects of demonetization, together provide a consistent account of the effects of demonetization.

5.1 Aggregate Time Series

Before presenting cross-sectional results, we first plot the aggregate time series in figure 6. The vertical line in each figure shows the period in which demonetization occurred.

Demonetization has a clear effect on aggregate ATM withdrawals and use of e-wallets

and POS payment technologies. These variables exhibit essentially no growth in the periods before demonetization and then a sharp contraction (ATM withdrawals) or increase (e-wallet and POS) exactly at the time demonetization occurred. The scale of the changes in these variables – a 50% decline in ATM withdrawals, a doubling of e-wallet transactions, and a sextupling of POS transactions between October and December 2016 – seem difficult to attribute to any economic shock other than demonetization.[20]

In contrast, the variables representing aggregate real economic activity – GDP growth, employment, and nightlights – do not exhibit clear patterns around demonetization, nor do bank deposits or credit.[21] Real GDP growth remained in the range 5.6-6.5 percent (annualized) in the four quarters surrounding demonetization. However, other economic shocks and policies besides demonetization affected the global economy and India specifically during this period. Salient examples include the election of Donald Trump which occurred on the same day as the demonetization announcement, a rise in the global price of crude oil of 60% from January to October 2016, a better Monsoon rainfall than in the previous year, increased uncertainty related to capital flows into Foreign Currency Non-Repatriable accounts and accompanying exchange rate volatility in November 2016, and an overhaul of the Indian sales tax collection system in the summer of 2017. Moreover, the official GDP measure misses much of the informal sector which relies heavily on cash and may have been especially impacted by demonetization. The absence of a clear break in the data and the existence of other shocks render aggregate trends uninformative for discerning the impact of demonetization on the real economy. Instead, we turn to cross-sectional differences.

5.2 Cross-sectional Specification

The cross-sectional approach has two crucial advantages relative to the aggregate time series plotted in figure 6. First, it holds constant other policies or shocks which affected the whole economy around the period of demonetization. Importantly, even if other policies or shocks had differential effects across subnational areas, the cross-sectional approach will still uncover the causal effect of demonetization as long as the demonetization shock is uncorrelated with these other variables. Second, instead of a single time series with a possible break in November 2016, the geographic variation in demonetization intensity generates a large

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[20]Because the wallet company provided us the data only in index format, the e-wallet panel of figure 6 shows an unweighted average across districts.

[21]Rural wage inflation (the only high frequency wage series available) and consumer price inflation remained positive and showed no discernible change in trend around demonetization. This is consistent with the model's assumption of downward wage and therefore price rigidity.

Figure 6: Aggregate Time Series

ATM Transactions

GDP

Employment/Population

Nightlights

E-Wallet

POS

Deposits

Credit
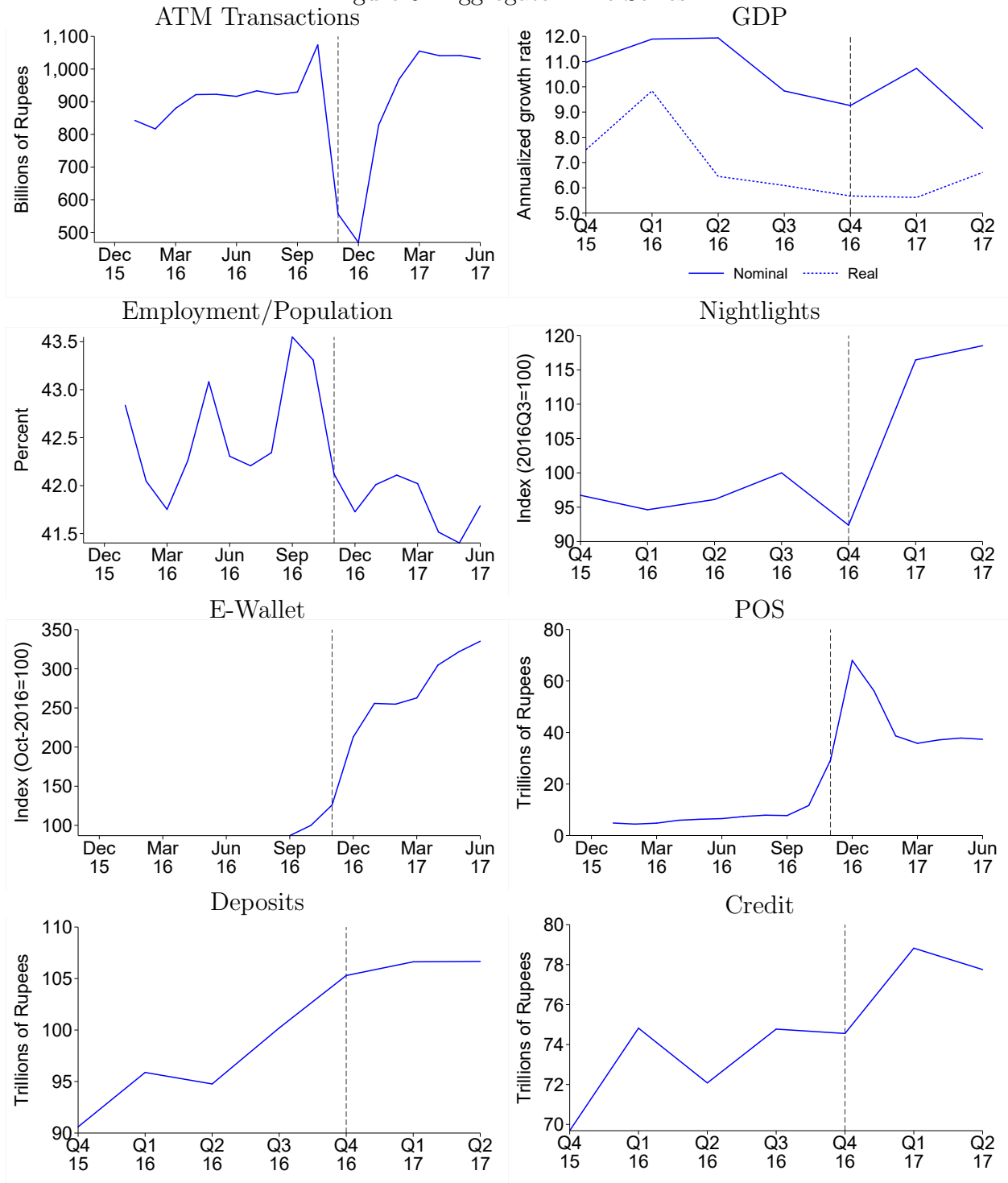
Notes: The dashed line in each figure denotes the month or quarter in which demonetization occurred.

sample with varying treatment intensity. The large sample makes possible tighter inference.

Our empirical specification is:

$$(y_{i,t} - y_{i,baseline}) = \beta_{0,t} + \beta_{1,t} z_{i,treatment} + \Gamma_t X_i + \epsilon_{i,t}, \tag{27}$$

where $y_{i,t} = \ln Y_{i,t}$ denotes the natural logarithm of an outcome variable, $y_{i,baseline} = \ln Y_{i,baseline}$ denotes the value of the variable in the period immediately preceding demonetization, i.e. October 2016 for monthly frequency data and 2016Q3 for quarterly frequency data, $z_{i,t} = \ln Z_{i,t}$ is the log of the demonetization shock, $z_{i,treatment}$ is set to $z_{i,t}$ for $t \in \{\text{November 2016}, \text{December 2016}\}$ and the December 2016 value for all other periods, and X_i is a vector containing any controls. The coefficients $\beta_{1,t}$ trace out the cumulative response at various horizons t to the demonetization shock in December 2016.

We offer three comments on specification (27). First, this specification cannot disentangle contemporaneous from lagged effects of the demonetization shock in months after December 2016. Rather, the coefficient $\beta_{1,t}$ reflects both the persistence in $z_{i,t}$ which makes $z_{i,treatment}$ correlated with $z_{i,t}$ for months after December 2016 and true lagged effects of $z_{i,treatment}$ on outcomes. We do not attempt to separate these effects because the stability of the rank of a district in the cross-sectional distribution of shocks yields too little variation to separately identify contemporaneous from lagged effects.[22] Second, some of the dependent variables used in the analysis have wide tails. The log-log specification helps to reduce sensitivity to outliers. We further trim observations with dependent variable in the the top and bottom 0.5% of the distribution in the period of analysis. Third, we cluster standard errors by state to account for the spatial correlation in $Z_{i,t}$ shown in figure 5. This level of clustering results in about 30 clusters.[23] We follow the advice of Imbens and Kolesár (2016) and apply the "LZ2" correction to the standard errors and compute confidence intervals using a t-distribution with degrees of freedom suggested by Bell and McCaffrey (2002).[24] Imbens and

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[22]For example, the Spearman rank correlation of z_i for December 2016 and March 2017 is 0.78.

[23]India consists of 29 states and 7 union territories and we use the term "state" in the main text to refer to either. We assign districts in Telangana to the same cluster as districts in Andhra Pradesh (the former was carved out of the latter in 2014 and both states share a single RBI regional office located in Hyderabad), have no currency chest data for the territory of Dadra and Nagar Haveli, and exclude the territory of Chandigarh because it has $Z_{i,t} < 0$. Therefore, the regressions which follow have a maximum of 33 clusters. In specifications controlling for 2015 GDP per capita, we further drop the two union territories of Daman & Diu and Lakshadweep due to lack of GDP data.

[24]The LZ2 correction applies a small sample adjustment which exactly corrects for finite sample bias in the sample counterpart of $E[\epsilon_{i,t}\epsilon'_{i,t}]$ when the true sampling distribution of $\epsilon_{i,t}$ is i.i.d. The degrees of freedom for the t-distribution are chosen such that under homoskedasticity the first two moments of the distribution of the error covariance matrix coincide with the first two moments of a chi-squared distribution.

Figure 7: ATM Withdrawals
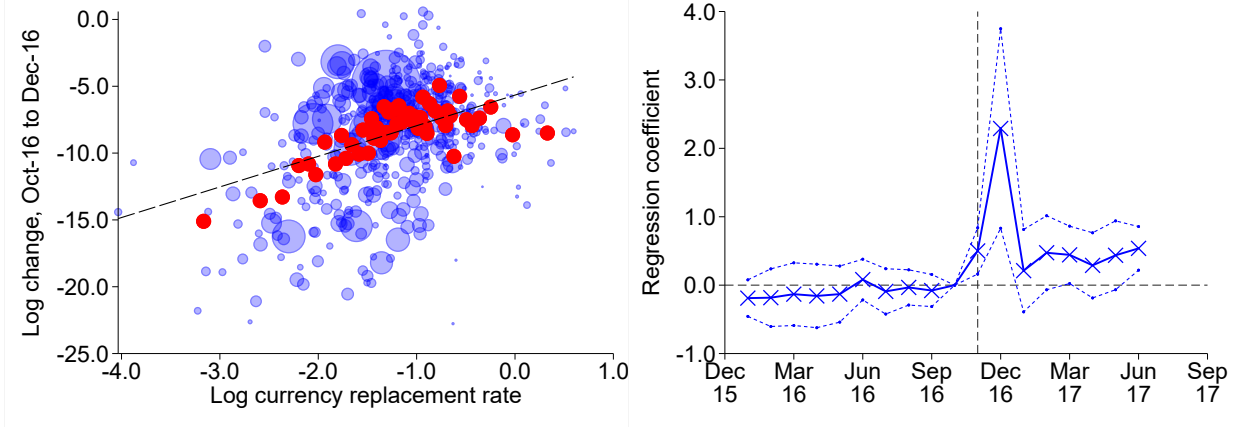
Notes: The left panel presents a scatter plot of the log change in ATM withdrawals between October 2016 and December 2016 and the log currency shock. The light blue circles show the raw data and are sized proportional to 2015 district GDP. The dark red circles average observations into 50 quantile bins of the currency shock. The dashed line gives the best fit line. The right panel reports the coefficient and 95% confidence interval from estimating equation (27) for the period indicated on the horizontal axis.

Kolesár (2016, table 4) present Monte Carlo evidence that the resulting confidence intervals have good coverage even with as few as five clusters or unbalanced cluster size.

5.3   Results

ATM withdrawals.   Figure 7 and table 5 show our first result – areas which received (proportionally) fewer new notes had sharper declines in ATM activity. The left panel provides a non-parametric representation of the data. The vertical axis gives the log change in ATM activity from October 2016, the last full pre-demonetization month, to December 2016, the first full month following demonetization. The horizontal axis shows $z_{i,t}$, the log of the average daily value in December 2016 of the demonetization measure described by equation (26). Each blue circle corresponds to a district, with the size of the circle proportional to 2015 district GDP. The red circles show the (unweighted) means of the change in ATM activity for each of 50 quantile bins of $z_{i,t}$. Thus, the figure overlays a so-called "binned scatter plot" on top of the raw data. The dashed red line shows the best fit line.

The right panel of figure 7 reports the coefficient from estimating equation (27) with no covariates in X_i for each month from November 2015 to June 2017. Thus, the value for December 2016 gives the slope of the best fit line in the figure in the left panel. The dashed lines show the (point-wise) 95% confidence intervals.

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Table 5: ATM Withdrawals

	(1)	(2)	(3)
Currency replacement	2.29**	2.28*	2.18*
	(0.66)	(0.75)	(0.76)
Log GDP per capita		−0.18	−0.10
		(0.80)	(0.72)
Agriculture share of GDP		0.02	−0.01
		(0.03)	(0.03)
Control lagged outcomes	No	Yes	Yes
Weight	No	No	Yes
Fitted 90-10 differential	36.5	36.4	34.7
Treatment BM df	10.7	11.3	12.5
R^2	0.14	0.17	0.16
Clusters	33	31	31
Observations	529	519	519

Notes: The dependent variable is the log point change from October 2016 to December 2016 multiplied by 10. Columns (2) and (3) additionally controls for 9 lags of the dependent variable. Column (3) weights the regression by district GDP. Standard errors in parentheses clustered by state using the "LZ2" bias-reduction modification suggested by Imbens and Kolesár (2016). **,*,+ denote significance at the 1, 5, or 10 percent level based on a t-distribution with degrees of freedom for the currency replacement variable shown in the row "Treatment BM df".

The figure shows a statistically strong, positive correlation between the arrival of new currency by December 2016 and ATM withdrawals. The link between money supply and cash withdrawals validates the usefulness of our geographic shock measure and provides *prima facie* evidence of a cash shortfall in which households are off their money demand curve. The near-zero values in the right panel for months before November 2016 indicate that districts which experienced larger demonetization shocks exhibited parallel trend growth of ATM withdrawals before the shock occurred. The cross-sectional impact of the shock on ATM withdrawals is concentrated in December 2016 but remains through June 2017. In terms of magnitude, the predicted difference in ATM withdrawals between districts at the 10th and 90th percentiles of the December 2016 shock distribution is 37 log points.

Table 5 demonstrates the robustness of the cross-sectional pattern. Column (1) reproduces the slope coefficient from the left panel of figure 7. Column (2) adds covariates to the regression: 2015 GDP per capita, the 2015 agriculture share of GDP, and nine lags of ATM transactions growth. The lags of ATM growth control directly for any pre-trends while the 2015 level of GDP per capita and agriculture share of GDP control for basic features of the industrial structure of Indian districts. Inclusion of these covariates has little effect on

the coefficient on $z_{i,t}$, consistent with the absence of correlation of $z_{i,t}$ with other variables shown in table 4. Column (3) weights the regression by district GDP. The coefficient changes little.[25]

Employment and nightlights. Figure 8 and table 6 display our next main result – demonetization reduced real economic activity. The scatter plots in the left panels of figure 8 show non-parametrically that areas with larger declines in currency experienced sharper declines in employment and in nightlight activity after demonetization occurred. The right panels show no evidence of pre-trends and highly statistically significant post-demonetization differences which last into the spring of 2017 before fully dissipating.[26]
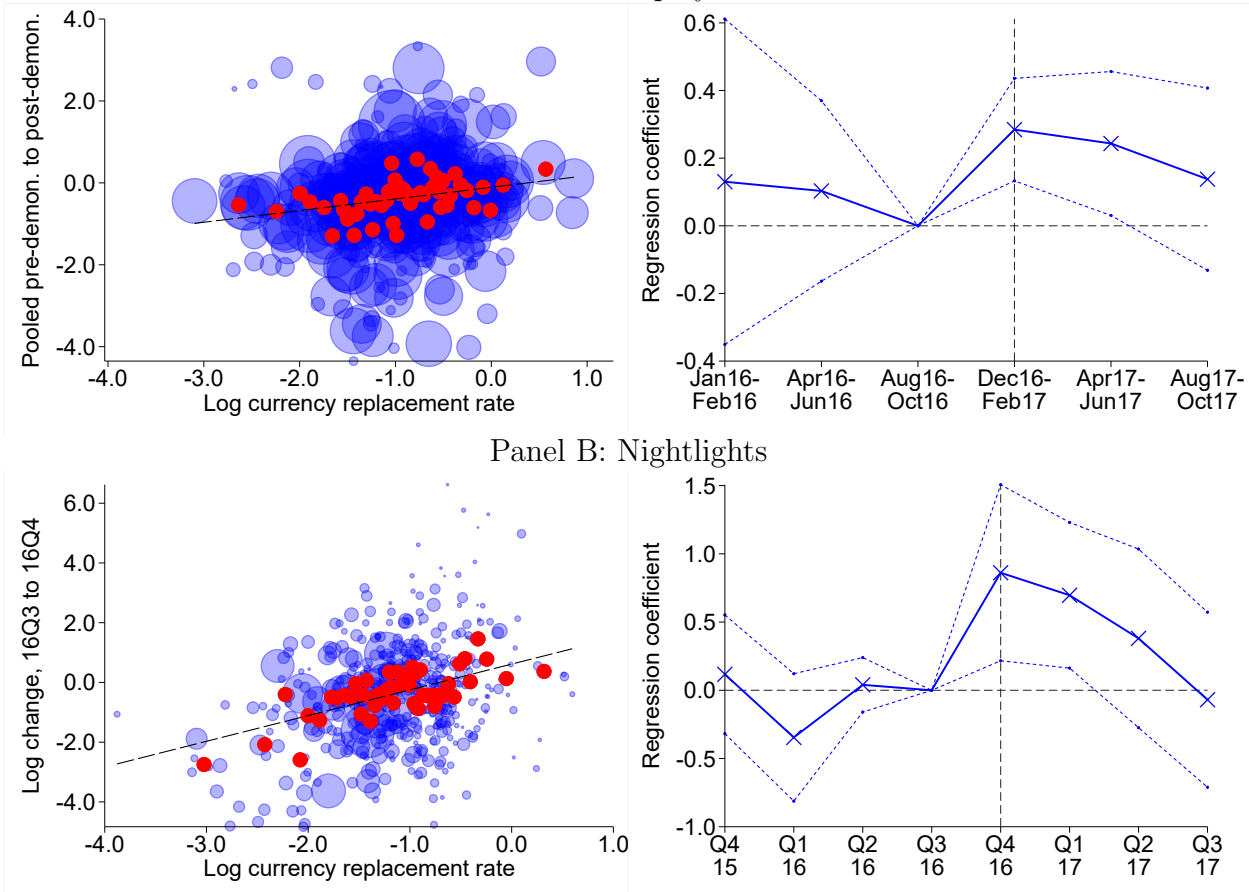
The magnitude of the effect on real activity is substantial. The predicted difference in employment growth between districts at the 10th and 90th percentiles immediately after demonetization is 4.6 log points while the predicted difference in nightlight growth is 14.3 log points.[27] Based on both annual and long-term growth rate comparisons for a sample of 188 countries, Henderson, Storeygard, and Weil (2012) argue for an elasticity of GDP growth to nightlight growth of 0.3. Their estimate remains similar even for a sub-sample of low and middle-income countries. Using this elasticity yields a predicted difference in GDP of roughly 4.4 log points. It bears emphasizing that these two measures of economic activity come from very different sources – a household survey of employment status and satellite measures of nightlight activity – yet they suggest quantitatively similar declines in output. The two measures together therefore provide powerful evidence of a link between money and output during demonetization.

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[25]Weighting would be appropriate if larger districts had less measurement error or if the effect of a given amount of demonetization varied with district size. The stability of the standard error in the weighted specification militates against the efficiency rationale. The small change in the point estimate suggests that weighting due to heterogeneous treatment effects is unnecessary.

[26]Recall that the employment survey uses a rotation schedule such that each month contains data for only about 150 districts. For this reason, the top left panel of table 6 pools observations from December 2016, January 2017, and February 2017 in order to obtain a more complete sample of districts and the top right panel shows coefficients grouping months with the same sample units. Because the data start in January 2016, the first point shown in the top right panel contains data from two rather than three months, explaining the wider confidence interval around that point.

[27]Technically, the predicted difference in the growth rate of the employment-to-population ratio is 4.6 log points. Recall that the household survey data from which we calculate the employment-to-population ratio do not permit measurement of the change in population. Assuming zero effect of demonetization on population, the predicted difference in the growth rate of the employment-to-population ratio is also the predicted difference in the growth rate of employment. We believe such an assumption to be reasonable given the short time horizon over which demonetization occurred. Nonetheless, if in fact more severe demonetization in an area led to worker outflows, then the effect on employment would be *larger* than the 4.6 log point difference given in the main text.

Figure 8: Real Activity
Panel A: Employment

Panel B: Nightlights

Notes: The top left panel presents a scatter plot of the log change in the employment-to-population ratio relative to the last observation before November 2016 and the log currency shock and pools observations from December 2016, January 2017, and February 2017. The bottom left panel presents a scatter plot of the log change in nightlight activity between July to September 2016 and November-December 2016 and the log currency shock. The light blue circles show the raw data and are sized proportional to 2015 district GDP. The dark red circles average observations into 50 quantile bins of the currency shock. The dashed line gives the best fit line. The right panels report the coefficients and 95% confidence intervals from estimating equation (27) for the period indicated on the horizontal axis.

The remainder of table 6 illustrates the robustness of the employment and nightlight results. Columns (2) and (5) show robustness to controlling for lagged outcomes and the level of GDP per capita and the agriculture sectoral share. Columns (3) and (6) show robustness to weighting or not. For employment, we weight the baseline specification by the number of individual-level observations in the district-month to reflect the construction of the district employment variable from individual-level data. Column (3) shows that not weighting increases the standard error substantially, consistent with a noisier measure of

Table 6: Real Activity

Dep. var.: log change in	Employment			Nightlights			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Currency replacement	0.28**	0.34**	0.19	0.90**	0.84**	0.97*	0.84**
	(0.07)	(0.07)	(0.12)	(0.29)	(0.26)	(0.36)	(0.23)
Log GDP per capita		0.19	0.04		−0.31	0.05	
		(0.10)	(0.21)		(0.22)	(0.27)	
Agriculture share of GDP		0.00	0.00		0.01	0.01	
		(0.00)	(0.00)		(0.01)	(0.01)	
Control lagged outcomes	No	Yes	Yes	No	Yes	Yes	No
Month span FE	No	Yes	Yes	No	No	No	No
Weight	Yes	Yes	No	No	No	Yes	No
Fitted 90-10 differential	4.6	5.5	3.1	14.3	13.4	15.4	13.3
Treatment BM df	9.9	10.1	10.4	12.7	15.2	10.8	10.9
R^2	0.03	0.30	0.23	0.10	0.50	0.43	0.09
Clusters	23	23	23	32	30	30	33
Observations	408	396	396	471	462	462	535

Notes: The dependent variable is the log point change from pre-demonetization to post-demonetization multiplied by 10. In columns (1)-(3) the sample pools all observations from December 2016 to February 2017. In columns (4)-(6) the sample includes observations from December 2016, excluding districts in Uttar Pradesh. Column (7) adds these districts to the sample. Columns (2), (3), (5), (6) additionally control for lags of the dependent variable. Columns (1) and (2) weight the regression by the number of individual observations in the district in the Consumer Pyramids data and column (6) weights the regression by district GDP. Standard errors in parentheses clustered by state using the "LZ2" bias-reduction modification suggested by Imbens and Kolesár (2016). **,*,+ denote significance at the 1, 5, or 10 percent level based on a t-distribution with degrees of freedom for the currency replacement variable shown in the row "Treatment BM df".

employment for districts with fewer individual observations. Finally, our baseline sample for nightlight activity only excludes districts in the state of Uttar Pradesh because they exhibit implausible growth of human-generated nightlights between 2016Q4 and 2017Q1. Column (7) shows that including these districts has essentially no effect on the estimated effect on nightlight activity in 2016Q4.[28]

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[28]The median quarterly growth rate among districts in Uttar Pradesh in 2017Q1 was 64 log points, equal to the 99th percentile quarterly growth rate for all other districts pooling over all quarters between 2015Q4 and 2017Q3. A possible explanation for the behavior of nightlights in 2017Q1 is that Uttar Pradesh held statewide elections in February and March of 2017 and the ruling party accelerated electrification in the run-up to the election.

Table 7: Alternative Forms of Payment, Dec-16

Dep. var.: log change in	E-Wallet			POS		
	(1)	(2)	(3)	(4)	(5)	(6)
Currency replacement	−2.13**	−2.21**	−2.60**	−2.55*	−2.15*	−1.54
	(0.39)	(0.38)	(0.44)	(0.89)	(0.96)	(1.32)
Log GDP per capita		−0.55	−0.17		−2.09*	−3.25**
		(0.54)	(0.43)		(0.91)	(0.91)
Agriculture share of GDP		0.01	0.01		0.16**	0.23**
		(0.01)	(0.01)		(0.02)	(0.03)
Control lagged outcomes	No	Yes	Yes	No	Yes	Yes
Weight	No	No	Yes	No	No	Yes
Fitted 90-10 differential	-34.0	-35.2	-41.4	-40.6	-34.3	-24.6
Treatment BM df	11.2	10.5	10.8	10.5	10.0	9.6
R^2	0.22	0.24	0.24	0.05	0.28	0.36
Clusters	30	29	29	33	31	31
Observations	510	502	502	520	498	498

Notes: The dependent variable is the log point change from October 2016 to December 2016 multiplied by 10. Columns (2), (3), (5), (6) additionally control for lags of the dependent variable. Columns (3) and (6) weight the regression by district GDP. Standard errors in parentheses clustered by state using the "LZ2" bias-reduction modification suggested by Imbens and Kolesár (2016). **,*,+ denote significance at the 1, 5, or 10 percent level based on a t-distribution with degrees of freedom for the currency replacement variable shown in the row "Treatment BM df".

POS and E-Wallet. The next set of results in figure 9 and table 7 show the shift to alternative payment technologies. Payments using both E-Wallet and POS increased more in districts experiencing sharper declines in money following demonetization. Thus, while these areas experienced declines in overall economic activity and ATM usage, they had faster growth of alternative payments mechanisms. This pattern strongly militates against the presence of an unobserved demand shock confounding our identification, as a pure demand shock would induce comovement across all payments mechanisms and output. While the e-wallet data start only in September 2016, limiting our ability to test for pre-trends, the POS data show no differential adoption during the pre-demonetization period. Both the e-wallet and POS coefficients imply an inter-decile difference of about 38 log points in the growth rate of alternative payment technologies between October 2016 and December 2016.

Table 7 shows robustness to the usual specification perturbations. The e-wallet results are highly robust and all statistically significant. The standard errors in the POS regressions are much larger, such that the coefficient on $z_{i,t}$ is insignificant in the weighted specification.

Figure 9: Alternative Forms of Payment
Panel A: E-Wallet
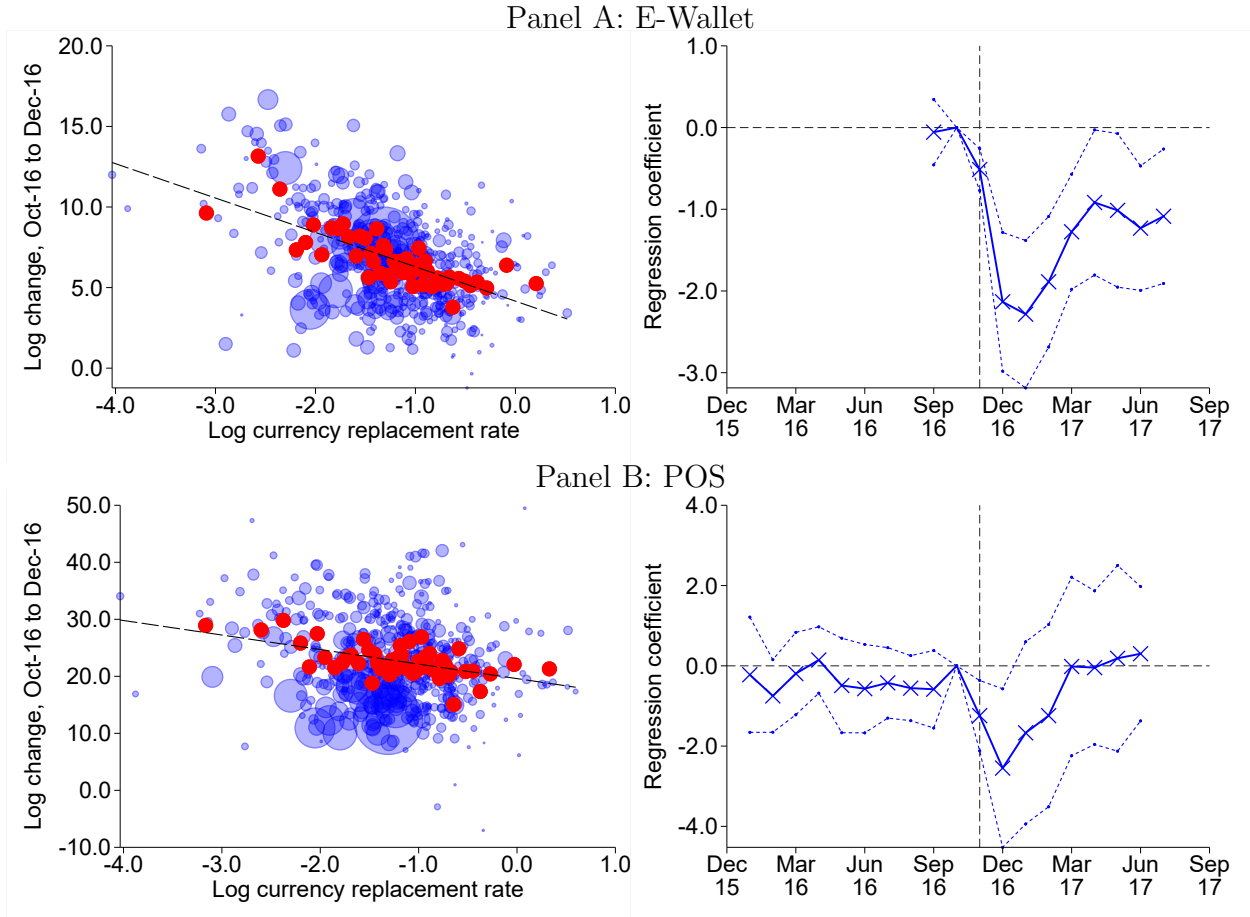
Panel B: POS

Notes: The left panels present scatter plots of the log change in e-wallet transactions (top row) or POS transactions (bottom row) between October 2016 and December 2016 and the log currency shock. The light blue circles show the raw data and are sized proportional to 2015 district GDP. The dark red circles average observations into 50 quantile bins of the currency shock. The dashed line gives the best fit line. The right panels report the coefficients and 95% confidence intervals from estimating equation (27) for the period indicated on the horizontal axis.

Deposits and Credit. Figure 10 and table 8 report our final set of results covering bank deposit and credit growth. We find evidence of bank deposits increasing and credit contracting in areas experiencing more severe demonetization. The effect on deposits appears short-lived while the effect on credit may be more persistent. Because banks have access to internal credit markets and banks in more-demonetized districts experienced faster deposit growth, we can interpret the contraction in lending in those districts as due to lower borrower demand for credit. As a caveat to these results, recall that the credit variable corresponds to loans made by banks within a district regardless of the location of the borrower. These results appear broadly robust to alternative specifications.

Figure 10: Bank Deposits and Credit
Panel A: Deposits
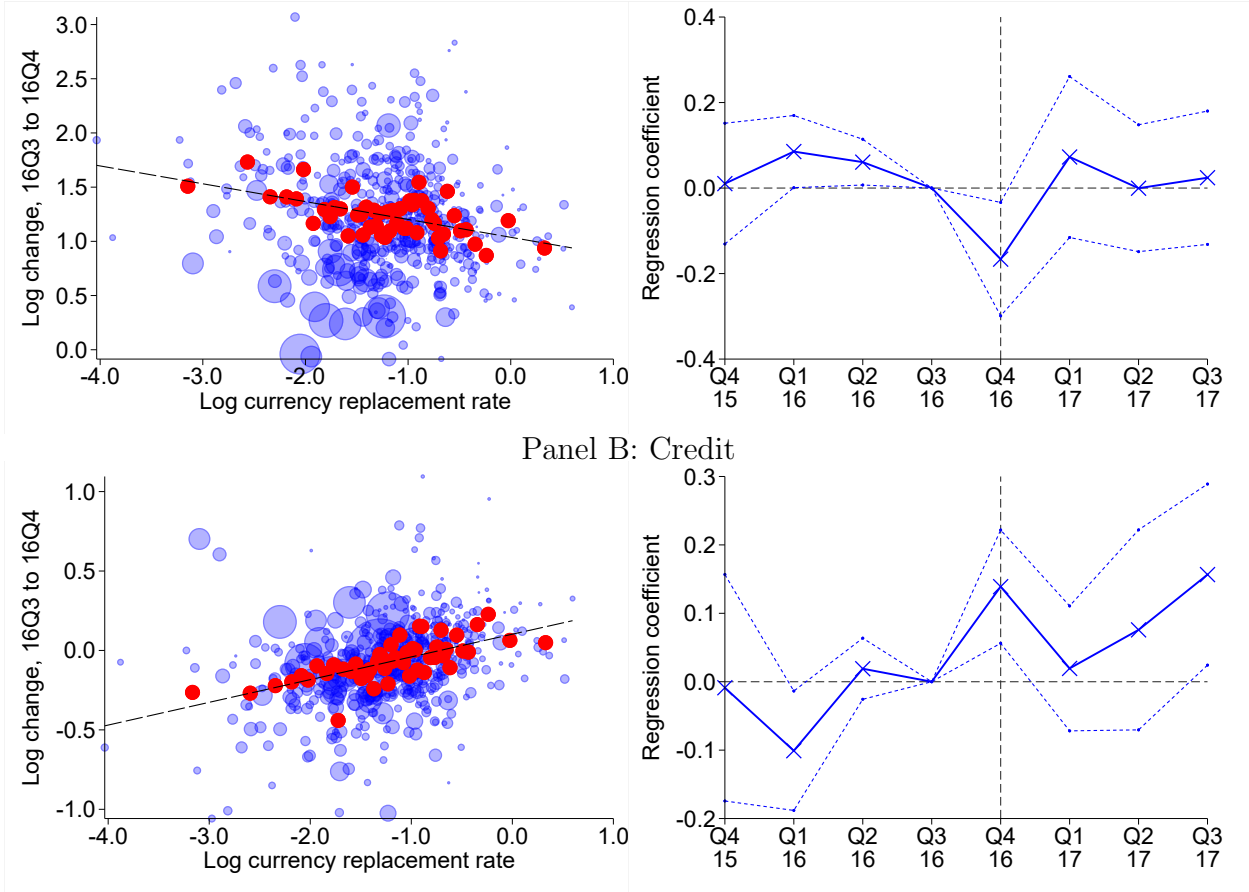
Panel B: Credit

Notes: The left panels present scatter plots of the log change in deposits (top row) or credit (bottom row)
between 2016Q3 and 2016Q4 and the log currency shock. The light blue circles show the raw data and are
sized proportional to 2015 district GDP. The dark red circles average observations into 50 quantile bins of
the currency shock. The dashed line gives the best fit line. The right panels report the coefficients and 95%
confidence intervals from estimating equation (27) for the period indicated on the horizontal axis.

Incorporating Lower Denomination Notes. Our baseline measure of the demonetiza-
tion shock $Z_{i,t}$ includes only new 2000 and 500 notes. In fact, the RBI also accelerated the
printing of lower denomination (100, 50, 20, 10, and 5) notes to help meet currency demand.
We calculate the value of lower denomination new notes using equation (23) applied to each
lower denomination note. In aggregate, less than 7% of total new notes which arrived at
chests between the start of demonetization and the end of December 2016 consisted of de-
nominations less than 500, yielding a cross-sectional correlation of $Z_{i,t}$ and a replacement
rate including net receipt of lower denomination notes above 0.99. As a result, incorporating
lower denomination notes has essentially no effect on the cross-sectional analysis, as shown

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Table 8: Bank Deposits and Credit, 2016Q4

Dep. var.: log change in	Deposits			Credit		
	(1)	(2)	(3)	(4)	(5)	(6)
Currency replacement	−0.17*	−0.18**	−0.14	0.14**	0.12**	0.06+
	(0.06)	(0.06)	(0.09)	(0.04)	(0.03)	(0.03)
Log GDP per capita		−0.20**	−0.27**		0.00	0.06
		(0.06)	(0.07)		(0.02)	(0.04)
Agriculture share of GDP		0.01**	0.02**		−0.00*	−0.00*
		(0.00)	(0.00)		(0.00)	(0.00)
Control lagged outcomes	No	Yes	Yes	No	Yes	Yes
Weight	No	No	Yes	No	No	Yes
Fitted 90-10 differential	-2.7	-2.8	-2.2	2.2	2.0	1.0
Treatment BM df	11.1	9.8	10.2	11.3	11.8	11.4
R^2	0.05	0.24	0.37	0.10	0.21	0.24
Clusters	32	30	30	32	30	30
Observations	529	520	520	529	519	519

Notes: The dependent variable is the log point change from 2016Q3 to 2016Q4 multiplied by 10. Columns (2), (3), (5), (6) additionally control for lags of the dependent variable. Columns (3) and (6) weight the regression by district GDP. Standard errors in parentheses clustered by state using the "LZ2" bias-reduction modification suggested by Imbens and Kolesár (2016). **,*,+ denote significance at the 1, 5, or 10 percent level based on a t-distribution with degrees of freedom for the currency replacement variable shown in the row "Treatment BM df".

formally in table 9.

6   Discussion and Relation to Aggregate Effect

The cross-sectional results establish that areas experiencing more severe demonetization had sharper declines in ATM withdrawals, reduced economic activity, faster adoption of alternative payment technologies, and higher deposit and lower bank credit growth. Among these results, the effect on real economic activity stands out in its contrast to the aggregate GDP time series. We now explore this difference in greater detail and what the cross-sectional evidence implies for the effect of demonetization on aggregate economic activity.

We start by cumulating the cross-sectional effects over districts. This calculation involves using the cross-sectional coefficient to impute to each district the change in the outcome variable relative to if no change in money balances had occurred, i.e. $Z_{i,t} = 1$, and then

Table 9: Cross-sectional Elasticities Including Lower Denomination Notes

Dep. var.	Baseline		Including lower denomination notes	
	$\beta_{1,t}$	s.e.	$\beta_{1,t}$	s.e.
ATM withdrawals	2.29**	0.66	2.35**	0.62
Employment	0.28**	0.07	0.28**	0.07
Nightlights	0.90**	0.29	0.85**	0.29
E-Wallet	−2.13**	0.39	−2.05**	0.41
POS	−2.55*	0.89	−2.52*	0.91
Deposits	−0.17*	0.06	−0.15*	0.07
Bank credit	0.14**	0.04	0.13**	0.04

Notes: The left panel reproduces the coefficients without controls in tables 5 to 8. The right panel reports the corresponding coefficients based on a measure of the demonetization shock $z_{i,t}$ which includes receipt of all denominations of notes in the numerator. Standard errors clustered by state using the "LZ2" bias-reduction modification suggested by Imbens and Kolesár (2016). **,*,+ denote significance at the 1, 5, or 10 percent level based on a t-distribution with degrees of freedom for the currency replacement variable shown in the row "Treatment BM df".

summing over districts. The formula for the cumulated effect in month t is:

$$\frac{\sum_{i:Z_{i,t}\leq 1}\left(e^{\beta_{1,t}z_{i,t}}-1\right)Y_{i,baseline}}{\sum_i Y_{i,baseline}} \approx \frac{\beta_{1,t}\sum_{i:Z_{i,t}\leq 1}z_{i,t}Y_{i,baseline}}{\sum_i Y_{i,baseline}}. \tag{28}$$

Using the coefficients show in columns (1) and (4) of table 6, for employment this calculation yields a decline of 3.7 p.p., while for nightlights this calculation yields a decline of 11.7 p.p. which translates into an output decline of 3.5 p.p. after applying the 0.3 elasticity advocated by Henderson, Storeygard, and Weil (2012).

Importantly, the preceding calculation assumes a log-linear relationship between the cash shortage and outcome variables. While the scatter plots shown above appear consistent with such linearity, because essentially all districts experienced a large decline in currency we lack the power to test for a non-linearity or kink at small declines in cash. Nonetheless, assuming instead a flat relationship (no effect of the cash shortage on outcomes) above a 0.9 replacement rate would only change the implied decline in employment to 3.3 p.p. and the decline in nightlights to 10.8 p.p. Similarly, accounting for the introduction of new lower denomination notes would raise the replacement rate and hence lower the cumulated cross-sectional shortfall by about 7%, yielding for example an implied decline in employment of $0.93 \times 3.7 = 3.4 p.p.$

The next step is to relate the cumulated quantity defined in equation (28) to the ac-

tual national effect. To do so we return to the model of section 3. There, the cumulated decline in output provides a *lower bound* for the true aggregate decline. The lower bound arises because of the tradeables sector; some of the demand shortfall in a local area gets exported to other areas through trade linkages. This logic closely relates to theoretical results presented in Nakamura and Steinsson (2014), Farhi and Werning (2016), and Chodorow-Reich (Forthcoming) in the context of estimation of cross-sectional fiscal multipliers. In the demonetization context the lower bound is especially sharp because national interest rates remained fixed and total government liabilities did not change.

Applying the lower bound result to the cross-sectional estimates for employment and nightlights, we conclude that demonetization caused a decline in national economic activity of roughly 3 p.p. or more in November and December 2016 relative to a no-demonetization counterfactual.[29] Similarly, the effect on credit implies a 2 p.p. or more decline in 2016$Q4$. These effects dissipate over the few months.

Is such a decline large? The magnitude of the peak effect on output makes demonetization comparable to a roughly 200 basis point tightening of the monetary policy rate based on the median of estimates reviewed in Ramey (2016) of econometric studies of U.S. data. Moreover, it implies a rejection of the cashless limit wherein all that matters in the conduct of monetary policy is the interest rate. On the other hand, the output decline is an order of magnitude smaller than the decline in cash itself. This difference illustrates the Lucas (1976) critique in action – in response to a change in policy, agents endogenously adjust (changing κ in our model) rather than passively obeying a pre-existing CIA constraint.

Why does the decline in output not obviously materialize in the national GDP data? As already mentioned, national data are volatile and subject to other shocks, making it difficult to discern a single break point around demonetization. Moreover, our measures of real activity have the advantage over official GDP of directly incorporating informal sector activity. The informal sector in India is estimated to account for 81% of total employment (ILO, 2018) and 44% of total output (CSO, 2018) and is especially cash-intensive. While the level of official GDP includes an estimate of informal sector activity derived from a quinquennial household survey, quarterly changes in GDP do not reflect any direct measurement of informal sector activity. Thus, our results also point to the likelihood of an absolute decline in

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[29]The aggregated changes in ATM withdrawals, e-wallet transactions, and POS transactions from applying equation (28) are also all smaller than the actual aggregate changes. However, some special factors apply to these variables. Many ATMs temporarily went out of service to receive recalibration required to dispense the new notes, independent of cash availability. Increasing returns to scale of payments technologies, information network effects, and increased advertising all may have contributed to a common component of adoption of alternative payments technologies across areas.

economic activity at the end of 2016 not captured in official statistics.[30]

In conclusion, we emphasize that we focus in this paper on the near term impact of demonetization. Our identification strategy based on random shocks to the cross-section of districts best lends itself to near term analysis because these cross-sectional differences dissipate in the months following demonetization. There may be longer term advantages from demonetization that arise from improvements in tax collections and in a shift to savings in financial instruments and non-cash payment mechanisms. Evaluating these long-term consequences requires waiting for more data and an empirical strategy suited to the study of longer term effects.

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[30]In the context of our model, aggregate economic activity must have declined if the wage constraint was binding. If trend growth in India was 1.5% per quarter (6% per year), then our estimates imply an absolute decline in economic activity of about 0.5% in 2016Q4 from the previous quarter. This follows from the 3% decline in November and December and no impact in the pre-demonetization month of October.

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Cash and the Economy:
Evidence from India's Demonetization

Online Appendix

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A   Model Proofs

Proof of proposition 1

Begin by assuming $\theta_{-1} = 0$, we will later derive the parameter restrictions under which this is the case. From the F.O.C. for cash in the steady state, we have that:

$$\eta_{-1} = \frac{1}{\nu} \log \left(\frac{\nu \bar{\tau}}{1 - \beta} \right)$$

From the definition of η it the follows that:

$$W_{-1} = \frac{M_{-1}}{N_{-1} \eta_{-1}}$$

From the F.O.C. for consumption in a zero inflation steady state it follows that real consumption is constant which implies that labor is constant. This further implies that wages are constant so the downward nominal rigidity is not binding and the economy is in full employment, i.e. $N_{-1} = \bar{N}$

Now, again using the definition of η_{-1} and the firms optimality conditions we have:

$$W_{-1} = \frac{M_{-1}}{\bar{N} \eta_{-1}}, \qquad P^T_{-1} = P^N_{-1} = (1 + \varphi(\beta^{-1} - 1)) \frac{M_{-1}}{\bar{N} \eta_{-1}}$$

As prices for both types of goods are the same, using the F.O.C. for tradable and non-tradable goods we have that:

$$\frac{C^N_{-1}}{C^T_{-1}} = \frac{1 - \alpha}{\alpha}$$

1

Applying market clearing conditions, $C_{-1}^T = N_{-1}^T$, $C_{-1}^N = N_{-1}^N$, $N_{-1}^N + N_{-1}^T = \bar{N}$ and rearranging yields:

$$N_{-1}^N = (1-\alpha)\bar{N}, \qquad N_{-1}^T = \alpha\bar{N}$$

From where point 1 follows immediately. For the remaining part of point 2 take the optimal price of the non-tradable good producer, multiply both sides by $(1-\alpha)\bar{N}$ and use the market clearing condition for this good:

$$P_{-1}^N C_{-1}^N = (1-\alpha)(1+\varphi(\beta^{-1}-1))\frac{M_{-1}}{\eta_{-1}}$$

Using the bundling condition for non-tradable goods and rearranging yields point 2:

$$\frac{M_{-1}}{P_{-1}} = \frac{\eta_{-1}C_{-1}}{1+\varphi(\beta^{-1}-1)}$$

It is only left to show that indeed $\theta_{-1} = 0$. We may rearrange this last expression as:

$$P_{-1}C_{-1} = (1+\varphi(\beta^{-1}-1))\frac{M_{-1}}{\eta_{-1}}$$

Now the cash-in-advance constraint being slack can equivalently be stated as:

$$\kappa(1+\varphi(\beta^{-1}-1)) < \eta_{-1}$$

And substituting the value for η_{-1}:

$$\kappa(1+\varphi(\beta^{-1}-1)) < \frac{1}{\nu}\log\left(\frac{\nu\bar{\tau}}{1-\beta}\right)$$

A restriction on parameters that we impose.

Proof of proposition 2

Start by assuming that both the cash-in-advance constraint and the downward nominal rigidity are binding. Now using the cash-in-advance constraint, the bundling condition for

the non-tradable good, and the market clearing condition for this good we find that:

$$\kappa \frac{P_0^N N_0^N}{1 - \alpha} = M_0$$

$$\Leftrightarrow N_0^N = \frac{(1 - \alpha) M_0}{\kappa P_0^N}$$

Using the optimality condition for the producer of the non-tradable good, the nominal rigidity, and the fact that interest rates remain constant, we can substitute for the price of the non-tradable good and obtain:

$$N_0^N = \frac{M_0}{\gamma M_{-1}} \cdot \frac{\eta_{-1}}{\kappa(1 + \varphi(\beta^{-1} - 1))}(1 - \alpha)\bar{N}$$

$$= \frac{Z}{\gamma} \cdot \frac{\eta_{-1}}{\kappa(1 + \varphi(\beta^{-1} - 1))}(1 - \alpha)\bar{N}$$

And through the same procedure:

$$N_0^T = \frac{Z}{\gamma} \cdot \frac{\eta_{-1}}{\kappa(1 + \varphi(\beta^{-1} - 1))}\alpha\bar{N}$$

Finally:

$$\frac{Y_0}{Y_{-1}} = \frac{Z}{\gamma} \cdot \frac{\eta_{-1}}{\kappa(1 + \varphi(\beta^{-1} - 1))}$$

Which proves point 1. Aggregate price level is given by:

$$P_0 = \frac{(1 + \varphi(\beta^{-1} - 1))\gamma W_{-1}}{\alpha^\alpha(1 - \alpha)^{1-\alpha}}$$

Now, real lending to firms is given by:

$$\frac{B_0^f}{P_0} = \frac{\alpha^\alpha(1 - \alpha)^{1-\alpha}\varphi N_0}{1 + \varphi(\beta^{-1} - 1)}$$

Similarly:

$$\frac{B_{-1}^f}{P_{-1}} = \frac{\alpha^\alpha(1 - \alpha)^{1-\alpha}\varphi\bar{N}}{1 + \varphi(\beta^{-1} - 1)}$$

Since $N_0 < \bar{N}$,

$$\frac{B_0^f}{P_0} < \frac{B_{-1}^f}{P_{-1}}$$

It is only left then to show that demonetization makes the downward nominal rigidity and

the cash-in-advance constraint binding. Multiplying both sides of the optimality condition of non-tradable goods producer by $C_{i,0}^N = N_0^N$ yields:

$$P_0^N C_0^N = (1 + \varphi(\beta^{-1} - 1))N_0^N W_0^N$$

. Now, using the cash-in-advance constraint and the bundling condition for non-tradable goods we find that:

$$(1 - \alpha)\frac{M_{i,0}}{\kappa} = (1 + \varphi(\beta^{-1} - 1))N_0^N W_0$$

Since demonetization is homogeneous, regional trade balances remain at zero so we may use the same procedure for tradeable goods to find that:

$$\alpha\frac{M_0}{\kappa} = (1 + \varphi(\beta^{-1} - 1))N_0^T W_0$$

Adding these two up, using labor markets' clearing condition and rearranging yields:

$$W_0 = \frac{M_0}{\kappa(1 + \varphi(\beta^{-1} - 1))N_0}$$

Now we derive the condition under which if $N_0 = \bar{N}$ then $W_0 < \gamma W_{-1}$:

$$\frac{M_0}{\kappa(1 + \varphi(\beta^{-1} - 1))\bar{N}} < \frac{\gamma M_{-1}}{\bar{N}\eta_{-1}}$$
$$\Leftrightarrow Z\frac{\eta_{-1}}{\kappa(1 + \varphi(\beta^{-1} - 1))} < \gamma$$

Under this conditions $N_0 < \bar{N}$ and $W_0 = \gamma W_{-1}$ as in point 3. Finally, for the cash-in-advance constraint to hold, we have that:

$$\frac{\kappa}{M_0} = \lambda_0 + \kappa\theta_0$$
$$\lambda_0(1 + \tau'(\eta_{i,0})) = \beta\lambda_1$$

Notice that we have used the fact that the cash-in-advance constraint is not expected to bind in $t > 0$. From these two equations it follows that:

$$\theta_0 = \frac{1}{M_0} - \frac{\beta\lambda_{i,1}}{\kappa(1 + \tau'(\eta_0))}$$

From the problem at $t = 1$ we have that:

$$\lambda_1 = \frac{\eta_1}{(1 + \varphi(\beta^{-1} - 1))M_1}$$

Now, rearranging, we find that $\theta_0 > 0$ may equivalently be written as:

$$\frac{M_1}{M_0} > \frac{\beta\eta_1}{\kappa(1 + \tau'(\eta_0))(1 + \varphi(\beta^{-1} - 1))}$$

Then, given this parameter restrictions, the cash-in-advance constraint is binding at $t = 0$.

Proof of proposition 3

We will again start by assuming that the downward nominal rigidity is binding and then show conditions under which this is the case. We now have that in every region the optimality condition for the producers of the non-tradable good is given by:

$$P_{i,0} = (1 + \varphi(\beta^{-1} - 1))\gamma W_{-1}$$
$$= (1 + \varphi(\beta^{-1} - 1))\gamma \frac{M_{-1}}{\eta_{-1}\bar{N}}$$

Multiplying both sides by $C_{i,0} = N_{i,0}^N$, using the cash-in-advance constraint, and the bundling condition for the non-tradable good yields:

$$(1 - \alpha)\frac{M_{i,0}}{\kappa} = (1 + \varphi(\beta^{-1} - 1))\gamma \frac{M_{-1}}{\eta_{-1}\bar{N}}N_{i,0}^N$$

Rearranging and using the definition of Z_i:

$$N_{i,0}^N = \frac{(1 - \alpha)Z_i}{\gamma}\frac{\eta_{-1}\bar{N}}{\kappa(1 + \varphi(\beta^{-1} - 1))}$$

As wages are constant across regions, so are the prices for tradeable varieties which implies that $C_{j,0}^T(\omega) = C_{j,0}^T$. Now, using the tradable good producers' optimality condition, the cash-in-advance constraint, and the bundling condition for tradable goods, it is possible to find that:

$$\frac{\alpha}{\kappa}Z_{j,0} = \frac{(1 + \varphi(\beta^{-1} - 1)\gamma)}{\bar{N}\eta_{-1}}C_{j,0}^T(i)$$

Integrating over j in both sides and using the market clearing condition for tradable variety i yields:

$$\frac{\alpha}{\kappa}Z = \frac{(1+\varphi(\beta^{-1}-1))\gamma}{\bar{N}\eta_{-1}}N_{i,0}^T$$

$$\Leftrightarrow N_{i,0}^T = \frac{\alpha Z}{\gamma}\frac{\eta_{-1}\bar{N}}{\kappa(1+\varphi(\beta^{-1}-1))}$$

Given these values for $N_{i,0}^T$ and $N_{i,0}^N$, and the production functions, point 1 in the proposition follows.

Point 2 follows directly from the fact that $B_{i,0}^f = \varphi\gamma W_{-1}N_{i,0}$ and $P_0 = \alpha^{\alpha}(1-\alpha)^{1-\alpha}(1+\varphi(\beta^{-1}-1))\gamma W_{-1}$. It is only left to prove that $W_{i,0} = \gamma W_{-1}$, i.e. the downward nominal rigidity is binding. The complementary slackness condition is given by:

$$(\bar{N} - N_{i,0})(W_{i,0} - \gamma W_{i,-1}) = 0$$

From point 1 we have that if:

$$\gamma > \left(\alpha Z + (1-\alpha)\tilde{Z}\right)\frac{\eta_{-1}}{\kappa(1+\varphi(\beta^{-1}-1))}$$

Where $\tilde{Z} = \max_j Z_j$, then $W_{i,0} = \gamma W_{-1}$ in every region i.

Numerical Illustration with Endogenous κ

We use the following functional forms: $\kappa(f) = \bar{\kappa}e^{-\zeta f}$ and $h(f) = \frac{a}{2}f^2$. Now it follows that $\theta_{i,0} = \frac{af_{i,0}}{\zeta M_{i,0}}$. Further:

$$\left(\frac{af_{i,0}-\zeta}{\zeta}\right)\kappa(f_{i,0})(1+\tau'(\eta_{i,0})) + \beta\lambda_{i,1}M_{i,0} = 0$$

$$\eta_{i,0} = \frac{Z_i}{\alpha\bar{Z} + (1-\alpha)Z_i}\kappa(f_{i,0})(1+\varphi(\beta^{-1}-1))$$

By substituting the second equation of this set in the first one we arrive at a single equation in $f_{i,0}$. We then have that, $f_{i,0} = \Psi(\mathcal{I}, Z_i)$ where $\mathcal{I}$ satisfies $\mathcal{I} = \int \psi(\mathcal{I}, Z_j)dj$. For the numerical solution we consider a discrete distribution for Z_i with finite support $\{Z_1, ..., Z_S\}$ and $\mathbb{P}(Z < Z_s) = w_s$, of course, $w_S = 1$. Notice that in this case $\mathcal{I} = \sum_{s=1}^{S}\frac{Z_s}{\kappa(f_{s,0})}\Delta w_s$. We
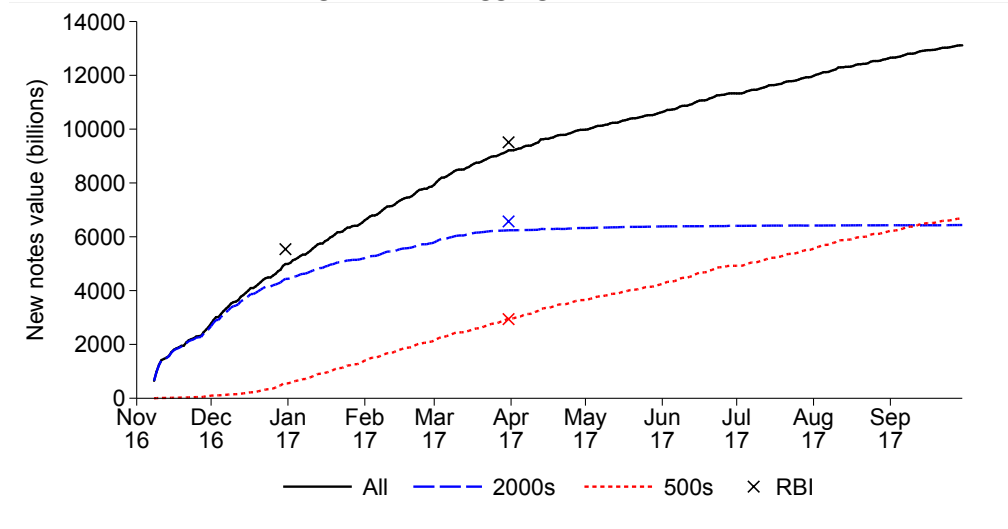
employ the parameter values shown in table A.1.

Parameter	Value
a	0.01
α	0.4
$\bar{\kappa}$	1
$\bar{\tau}$	0.2
β	0.98
γ	1
M_{-1}	1
M_1	1
$\bar{N}$	1
ν	2.5
φ	0.9
ζ	10

s	Z_s	w_s
1	0.0431	0.01
2	0.089	0.05
3	0.126	0.1
4	0.21	0.25
5	0.307	0.5
6	0.464	0.75
7	0.636	1

Table A.1: Parameter values

Figure B.1: Aggregate New Notes

Notes: The figure plots the aggregate value of new notes using our data and the definitions given in **??** and equation (23). For comparsion, the xs show the value of total new notes as stated in RBI (2017a, p. 124 and table VIII.1).

B   Data Benchmark

The currency chest data from the RBI is confidential and not publicly available. Figure B.1 plots the aggregate value of new notes in our data over time, using the definitions given in equation (22) and equation (23). For comparison, the xs show the value of new notes as stated in RBI (2017a). Our measures track the RBI official reporting extremely closely in both levels and differences.

C   Further Robustness

C.1   Chests Serving Multiple Districts

Currency chests can serve banks in multiple districts. In this appendix we show that measurement error arising from chests which serve multiple districts would attenuate the empirical results toward zero.

Recall our baseline cross-sectional specification:

$$\Delta y_{i,t} = \beta_{0,t} + \beta_{1,t} z_{i,treatment} + \Gamma_t X_i + \epsilon_{i,t}, \tag{C.1}$$

where $\Delta y_{i,t} = \ln Y_{i,t} - \ln Y_{i,baseline}$ denotes the change in the natural logarithm of an outcome variable relative to the period before demonetization, $z_{i,treatment} = \ln Z_{i,treatment}$ is the log of the demonetization shock, and X_i is a vector containing any controls. We construct $z_{i,treatment}$ by aggregating across currency chests in district i.

Now suppose $z_{i,treatment}$ is a noisy measure of the true demonetization shock, $z^*_{i,treatment}$,

$$z_{i,treatment} = z^*_{i,treatment} + e_i, \tag{C.2}$$

where the measurement error e_i is mean zero and independent of $z^*_{i,treatment}$. The measurement error e_i could for example stem from not adjusting for chests serving multiple districts. Thus, the true data generating process replaces $z_{i,treatment}$ in equation (C.1) with $z^*_{i,treatment}$:

$$\Delta y_{i,t} = \beta^*_{0,t} + \beta^*_{1,t} z^*_{i,treatment} + \Gamma^*_t X_i + \epsilon^*_{i,t}, \tag{C.3}$$

where $E[\epsilon^*_{i,t} e_i] = E[z^*_{i,treatment} \epsilon^*_{i,t} | X_i] = 0$.

To study the consequence of estimating equation (C.1) instead of equation (C.3), let $w^{\perp}_{i,t}$ denote the residual from projecting a variable w_i on a constant and X_i and *plim* the

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probability limit. Then the OLS coefficient $\hat{\beta}_{1,t}$ from estimating our baseline specification is:

$$
\begin{aligned}
plim\hat{\beta}_{1,t} &= \frac{\text{Cov}\left(\Delta y_{i,t}^{\perp}, z_{i,treatment}^{\perp}\right)}{\text{Var}\left(z_{i,treatment}^{\perp}\right)} \\
&= \frac{\text{Cov}\left(\Delta y_{i,t}^{\perp}, z_{i,treatment}^{*\perp} + e_i^{\perp}\right)}{\text{Var}\left(z_{i,treatment}^{*\perp} + e_i^{\perp}\right)} \\
&= \frac{\text{Var}\left(z_{i,treatment}^{*\perp}\right)}{\text{Var}\left(z_{i,treatment}^{*\perp} + e_i^{\perp}\right)} \frac{\text{Cov}\left(\beta_{1,t}^* z_{i,treatment}^{*\perp} + \epsilon_{i,t}^{*\perp}, z_{i,treatment}^{*\perp} + e_i^{\perp}\right)}{\text{Var}\left(z_{i,treatment}^{*\perp}\right)} \\
&= (1 - b) \times \beta_{1,t}^*,
\end{aligned}
\tag{C.4}
$$

where in the last line we define $b = \text{Var}\left(e_i^{\perp}\right)/\text{Var}\left(z_{i,treatment}^{*\perp} + e_i^{\perp}\right) \in [0, 1]$ as the attenuation bias coefficient which is the contribution of the measurement error to the overall variance in the measured demonetization shock (after partialling out covariates).

Using equation (C.4), we see that the estimated coefficient from our baseline specification equation (C.1) is equal to the product of $(1 - b)$ and the true coefficient $\beta_{1,t}^*$. Since $b \in [0, 1]$, we have the result that measurement error due to misclassification of flows to currency chests which serve multiple districts would bias our results toward zero. The only assumptions made are that the mismeasurement caused by chests serving multiple districts is uncorrelated with the true measure of cash shortage in each district and with the unobserved determinants of the outcome variable.

C.2 Lower Denomination Notes

In this appendix we report the main empirical outcomes using the measure of demonetization which includes newly printed lower denomination notes.

C.3 Seasonality in CMIE Data

Insufficient historical coverage (data start in 2016) and the sampling pattern of the CMIE data (not every district surveyed every month) make district-level seasonal adjustment of the CMIE data impossible. However, any aggregate seasonal pattern is "differenced out" in the cross-sectional estimation and affects only the constant term in the regression. There remains the issue of district-specific seasonality. Such seasonality is classical left-hand-side measurement error and will inflate the regression standard errors but not bias the point estimates. Formally, let $\Delta s_{i,t}$ denote the (demeaned) district-specific log change in the seasonal factor

Figure C.1: ATM Withdrawals Including Lower Denomination Notes in $Z_{i,t}$
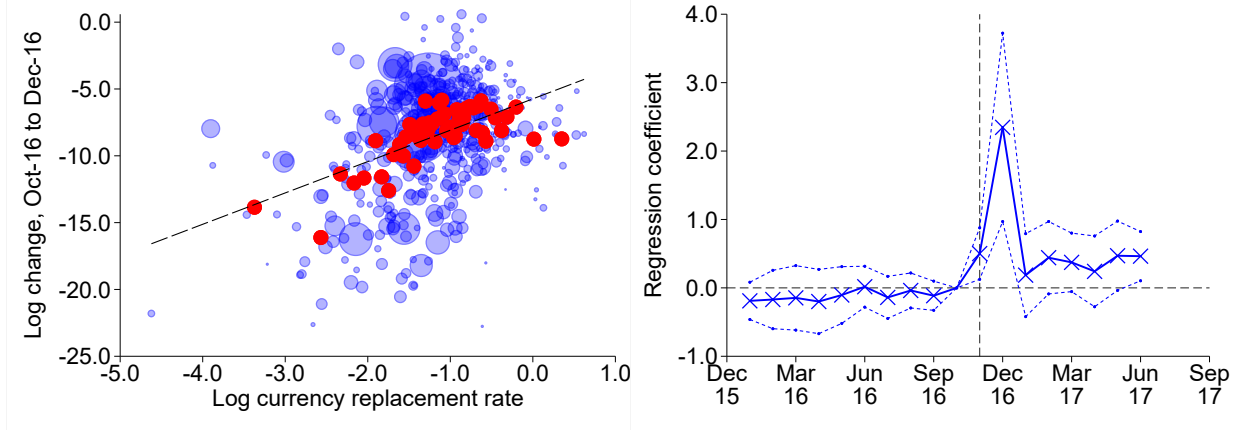
Notes: The left panel presents a scatter plot of the log change in ATM withdrawals between October 2016 and December 2016 and the log currency shock. The light blue circles show the raw data and are sized proportional to 2015 district GDP. The dark red circles average observations into 50 quantile bins of the currency shock. The dashed line gives the best fit line. The right panel reports the coefficient and 95% confidence interval from estimating equation (27) for the period indicated on the horizontal axis.

and $\Delta y_{i,t}^*$ (demeaned) seasonally-adjusted employment growth, so that $\Delta y_{i,t}^* = \Delta y_{i,t} + \Delta s_{i,t}$ with $E[\Delta s_{i,t} z_{i,treatment}] = 0$. Comparing the two regression models:

$$\Delta y_{i,t}^* = \beta_{0,t}^* + \beta_{1,t}^* z_{i,treatment} + \Gamma_t^* X_i + \epsilon_{i,t}^*, \tag{C.5}$$

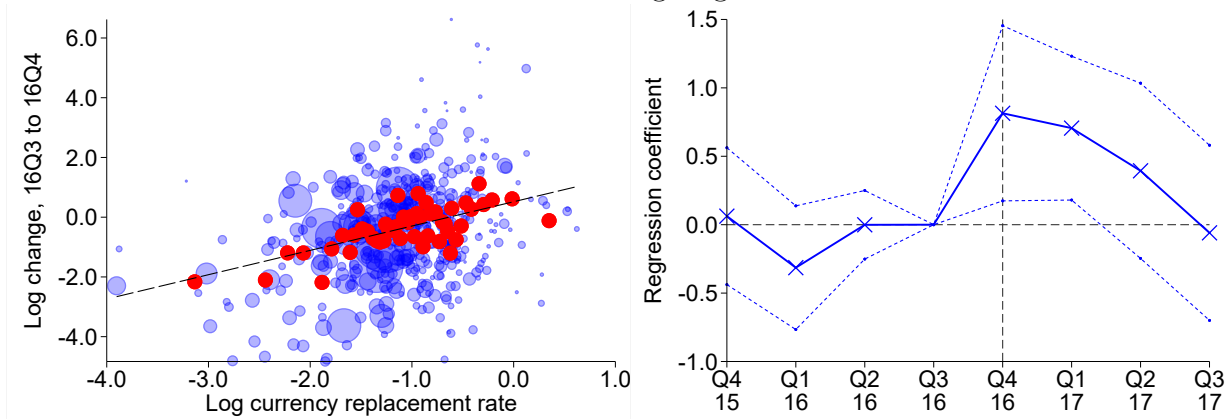$$\Delta y_{i,t} = \beta_{0,t} + \beta_{1,t} z_{i,treatment} + \Gamma_t X_i + \epsilon_{i,t}, \tag{C.6}$$

it is apparent that the second equation is equivalent to the first with $\epsilon_{i,t} = \epsilon_{i,t}^* - \Delta s_{i,t}$. Therefore, $plim\hat{\beta}_{1,t} = plim\hat{\beta}_{1,t}^*$, and $\text{Var}\left(\hat{\beta}_{1,t}\right) > \text{Var}\left(\hat{\beta}_{1,t}^*\right)$ because the residual variance is larger.

Figure C.2: Real Activity Including Lower Denomination Notes in $Z_{i,t}$

Panel A: Employment

Panel B: Nightlights

Notes: The top left panel presents a scatter plot of the log change in the employment-to-population ratio relative to the last observation before November 2016 and the log currency shock and pools observations from December 2016, January 2017, and February 2017. The bottom left panel presents a scatter plot of the log change in nightlight activity between July to September 2016 and November-December 2016 and the log currency shock. The light blue circles show the raw data and are sized proportional to 2015 district GDP. The dark red circles average observations into 50 quantile bins of the currency shock. The dashed line gives the best fit line. The right panels report the coefficients and 95% confidence intervals from estimating equation (27) for the period indicated on the horizontal axis.
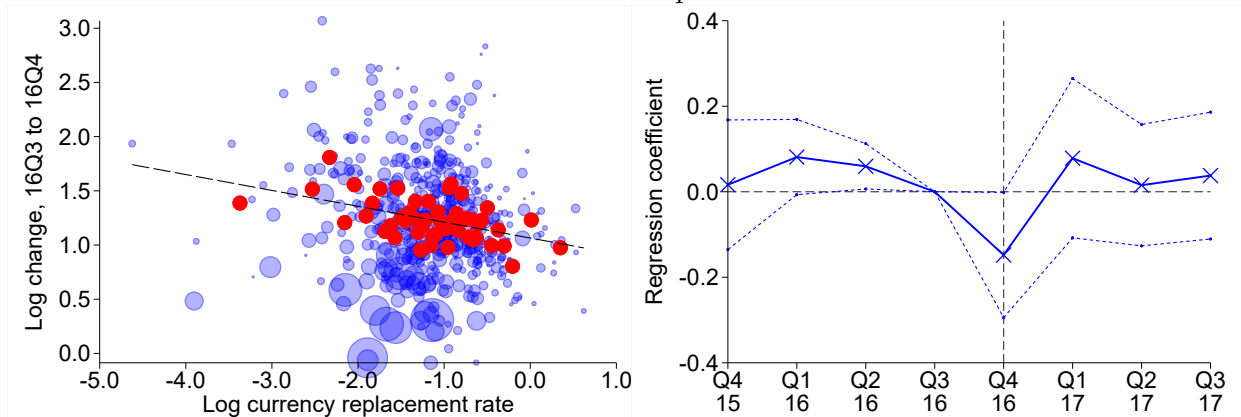
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Figure C.3: Alternative Forms of Payment Including Lower Denomination Notes in $Z_{i,t}$
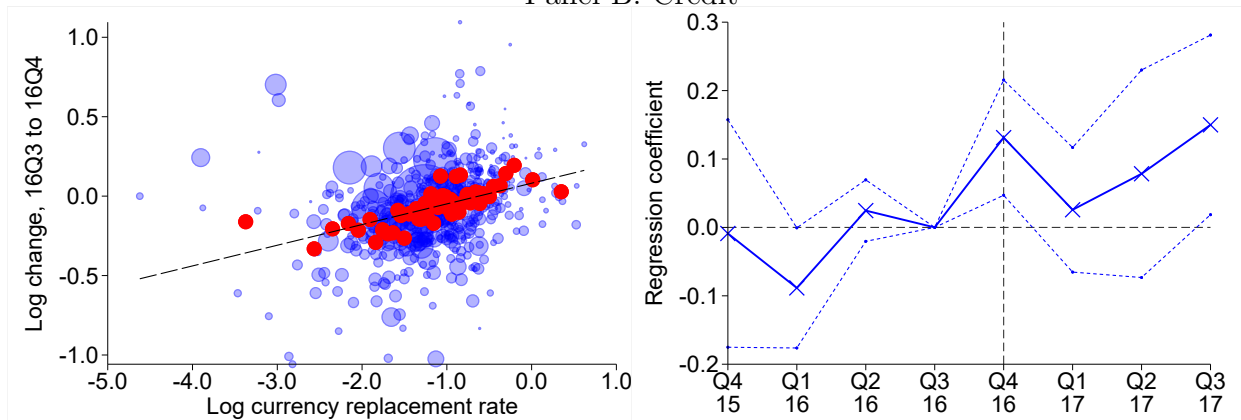
Panel A: E-Wallet
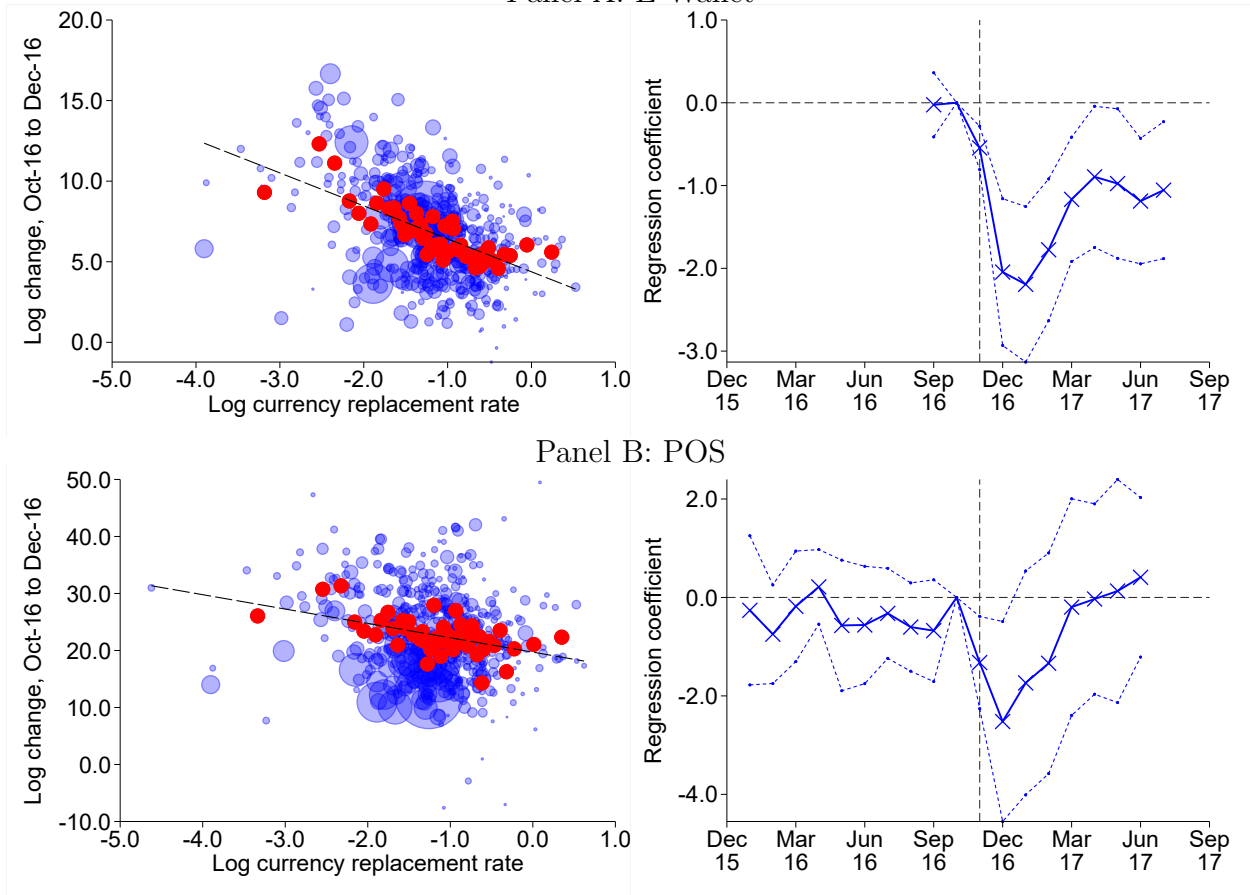
Panel B: POS

Notes: The left panels present scatter plots of the log change in e-wallet transactions (top row) or POS transactions (bottom row) between October 2016 and December 2016 and the log currency shock. The light blue circles show the raw data and are sized proportional to 2015 district GDP. The dark red circles average observations into 50 quantile bins of the currency shock. The dashed line gives the best fit line. The right panels report the coefficients and 95% confidence intervals from estimating equation (27) for the period indicated on the horizontal axis.

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Figure C.4: Bank Deposits and Credit Including Lower Denomination Notes in $Z_{i,t}$

Panel A: Deposits

Panel B: Credit

Notes: The left panels present scatter plots of the log change in deposits (top row) or credit (bottom row) between 2016Q3 and 2016Q4 and the log currency shock. The light blue circles show the raw data and are sized proportional to 2015 district GDP. The dark red circles average observations into 50 quantile bins of the currency shock. The dashed line gives the best fit line. The right panels report the coefficients and 95% confidence intervals from estimating equation (27) for the period indicated on the horizontal axis.