

CASH AND THE ECONOMY: EVIDENCE FROM INDIA'S DEMONETIZATION*

GABRIEL CHODOROW-REICH

GITA GOPINATH

PRACHI MISHRA

ABHINAV NARAYANAN

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: the geographic distribution of demonetized and new notes for causal inference; night light activity 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 aggregate employment and night lights-based output due to the cash shortage of at least 2 percentage points and of bank credit of 2 percentage points in 2016Q4 relative to their counterfactual paths, effects that dissipate over the next few months. Our analysis rejects monetary neutrality using a large-scale natural experiment, something that is still rare in the vast literature on the effects of monetary policy. *JEL* Codes: E41, E51, E52, E58, O17.

*We thank Martin Rama and Robert Carl Michael Beyer of the World Bank for sharing night lights data, Tilottama Ghosh at the Earth Observation Group at NOAA for clarifying many basic questions relating to the night lights data, National Payments Corporation of India for providing data on ATM and POS transactions, and Quantta for providing geocode coordinates. We thank Fernando Alvarez (discussant), Pol Antràs (associate editor), Vimal Balasubramaniam (discussant), Robert Barro (editor), Bent Sorenson (discussant), Ivan Werning, four anonymous referees, and numerous seminar participants for their comments. Gabriel Knigsberg and Anna Stansbury provided excellent research assistance. Gita Gopinath is economic counselor and director of research at the IMF. She contributed to this article before joining the IMF, when she was John Zwaanstra Professor of International Studies and of Economics at Harvard University. Mishra was employed at the IMF at the time this work was completed. The views expressed in this article are those of the authors and do not necessarily represent the views of the IMF, its executive board, IMF management, the Reserve Bank of India, Goldman Sachs, or any other institution with which the authors are affiliated.

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The Quarterly Journal of Economics (2020), 57–103. doi:10.1093/qje/qjz027.

Advance Access publication on September 10, 2019.

I. INTRODUCTION

Despite an impressive body of literature on the effects of monetary policy, large-scale natural experiments remain rare. In this article we study a unique episode known as demonetization. On November 8, 2016, the government of India unexpectedly declared 86% of the existing currency in circulation illegal tender, effective at midnight. Printing press constraints prevented the immediate replacement of the demonetized currency with new notes, with the result that cash that could be used in transactions declined sharply. Moreover, the arrival rate of new currency notes varied tremendously across geographic areas. 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.

We have two main findings. First, we reject monetary neutrality by providing well-identified, statistically strong evidence of an effect of money on output in the cross-section of Indian districts. Second, we shed light on why cash matters. In the New Keynesian synthesis (Woodford 2003), money serves only as a unit of account and outcomes depend only on the interest rate set by monetary policy, with the details of the money supply essentially irrelevant. During demonetization, cash declined while the sum of cash and checking deposits remained stable and market interest rates changed little. We therefore conclude that in modern India, cash plays a special role in facilitating transactions.

We first present a model of demonetization to guide the empirical analysis. In the model, agents hold cash for two reasons. First a cash-in-advance (CIA) constraint requires money holdings to pay for expenditures, along the lines of Lucas (1982), Lucas and Stokey (1987), and Svensson (1985). Second 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 noncash 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 alone cannot answer this question because they have limited coverage of the informal, cash-intensive sector of the economy, because the episode constitutes

only a single observation, 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 postdemonetization to predemonetization currency in an area. We present both narrative and statistical evidence that these demonetization shocks occurred essentially at random with respect to local 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 that experienced more severe demonetization shocks had much larger contractions in ATM withdrawals. The link between currency availability and cash withdrawals 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 sub-national level and at high frequency do not exist. We use a new household survey of employment and satellite data on human-generated night light activity to measure demonetization's effects at the district level. Importantly, these variables capture both formal and informal sector economic activity. The variables reveal 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, both variables map into a difference in output of roughly 4 percentage points between districts at the 10th and 90th percentile of the demonetization shock in the period immediately after the announcement. These results reject neutrality of money during demonetization.

Our third set of results demonstrate the adoption of alternative forms of payment technology in response to demonetization. Although the difference in output across districts is substantial, it is far less than the roughly 50 percentage point interdecile 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 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 nondemonetization demand shock would instead induce positive comovement across all payment mechanisms and output.

Finally, areas experiencing more severe cash shortages had higher deposit growth because households could not withdraw money from their bank accounts. Credit growth in these areas nonetheless slowed, providing additional corroborating evidence of an effect on real activity.

Our results imply that the decline in cash lowered the growth rate of economic activity by at least 2 percentage points in the quarter of demonetization. To reach this number, we cumulate the cross-sectional effects on employment and night lights over districts. Next, we argue that this calculation provides a lower bound for the aggregate consequences of the cash decline. Such a lower bound arises in our model due to cross-district trade. Combining these two results yields a decline in night lights-based economic activity and of employment of 3 percentage points or more in November and December 2016 relative to the counterfactual path, which translates into a decline in the quarterly growth rate of 2 percentage points or more. Similarly, the effect on credit implies a 2 percentage points or more decline in 2016Q4.¹ We conclude that in modern India, cash continues to serve an essential role in facilitating economic activity.

We review related literature next. [Section II](#) contains institutional details of demonetization. [Section III](#) presents the model and empirical predictions. [Section IV](#) describes the data, the construction of the geographic demonetization shocks, and the conditions for causal interpretation of the analysis. [Section V](#) presents the cross-sectional results. [Section VI](#) discusses the aggregate implications.

I.A. 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

1. These are nonannualized numbers, meaning that the 2016Q4 year-over-year growth rate declined by 2 percentage points as a result of the cash decline.

number of new data sets and a cross-sectional empirical approach to identify more credibly 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 \(2019\)](#). 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 eighteenth-century France, we study a sudden and very large decline in currency.

Our empirical results provide support for theoretical traditions that 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 CIA constraint. The “new monetarist perspective” ([Williamson and Wright 2010](#)) instead introduces asymmetric information, 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 that 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 \(2019\)](#) also examine the adoption of alternative payment technology during demonetization and, like us, find persistent effects of demonetization on e-wallet use. Whereas their work focuses on the network externalities of payment technologies, we emphasize the interplay between adoption of alternative means of payment and the effect on output.

2. [Lagos and Zhang \(2019\)](#) 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.

Last, our article sheds light on a debate around the possible benefits of 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 any phase-out of cash should take place slowly and with ample anticipation to allow households to adopt other forms of payment. Our results accord with these prescriptions.

II. DEMONETIZATION

On November 8, 2016, at 8:15 pm, the prime minister of India announced in an unscheduled, nationally televised address that the two largest denomination notes, the 500 (US \$7.5) and 1,000 rupee (US \$15) notes, would cease to be legal tender, to be replaced by new 500 and 2,000 rupee 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 (Modi 2016). 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 of old notes.⁴

Figure I shows the path of large (500 rupee and above) legal tender denomination notes as a share of total preannouncement currency outstanding, using the currency chest data described below. The old 500 and 1,000 rupee notes accounted for 86% of predemonetization currency. To maintain secrecy prior to the policy’s announcement, the government and RBI did not print and distribute a large quantity of new notes before the announcement. 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.⁵

4. The December 31 limit applied to ordinary note holders. Nonresident 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. Although all commercial banks and urban cooperative banks were allowed to accept deposits in old currencies, district cooperative banks were prohibited from doing so.

5. If large denomination notes circulate less rapidly, then the velocity-adjusted decline in currency would be smaller than what is shown in Figure I. Using aggregate data reported in RBI (2017a), we can estimate a velocity-adjusted share of large notes under the assumption that the spoilage rate—the rate at which notes

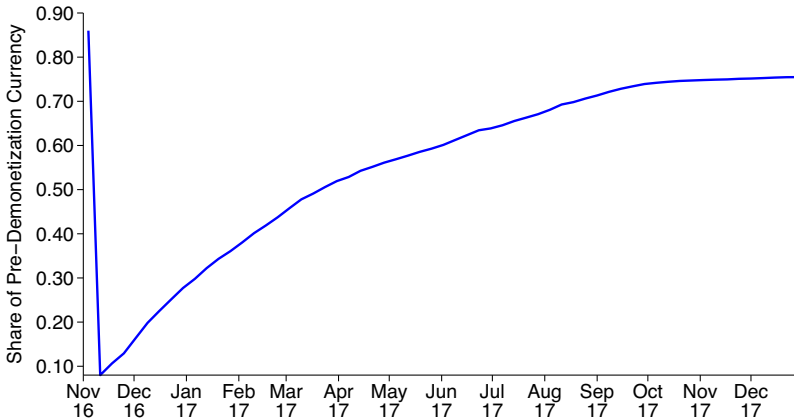


FIGURE I
Large-Denomination Legal Tender

The figure plots the value of old 500 and 1,000 notes (before November 8, 2016) and new 500 and 2,000 notes (after November 8, 2016) as a share of total currency in circulation on November 4, 2016 using the currency chest data described below.

Although 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 because of the cash shortage.⁶ The RBI initially required banks to hold these deposits as reserves at the RBI by increasing the cash reserve ratio

are returned to the RBI for destruction because of wear-and-tear—is proportional to velocity. In March 2016, this calculation yields a velocity-adjusted large-note share of 76%.

6. 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 4,000 (\$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 2,000 (\$30) per day per card (RBI 2016). These limits were progressively relaxed and finally removed on January 30, 2017. The RBI carved out exceptions for special circumstances, such as weddings. In addition, 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 et al. (2018) document general confusion about deposit and withdrawal limits caused by these many rules changes. Our focus in

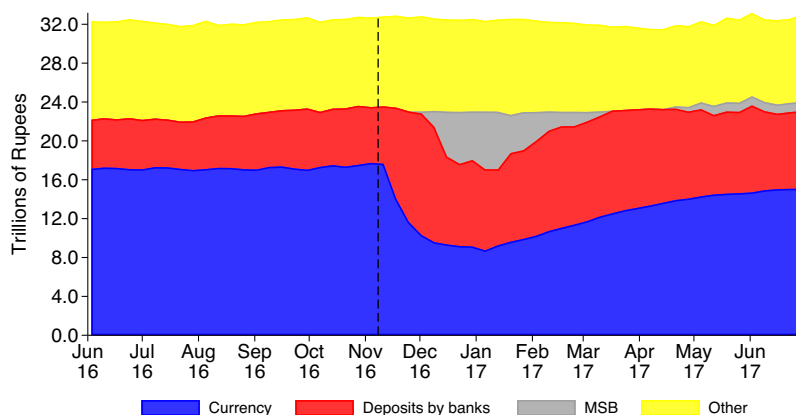


FIGURE II
RBI Liabilities

to 100% on all incremental deposits received between September 16 and November 11. Because 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 (MSBs).⁷ Figure II shows the overall stability of RBI liabilities and the initial increase in commercial bank deposits, later replaced by MSB issuance.⁸ 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 might lead to the liquidation of a portion of the RBI's currency liabilities.⁹ Thus, demonetization

this article concerns the total cash available for withdrawal and not how account limits affected the distribution of withdrawals across households.

7. 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 14 to 42 days.

8. The currency liabilities shown in Figure II decline more gradually than the sharp drop in legal tender shown in Figure I. 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.

9. According to the RBI (2018), 99% of total 500 and 1,000 rupee notes in circulation prior to demonetization were returned to the RBI. Moreover, the demonetized notes came back fairly quickly. Recall that most people had until

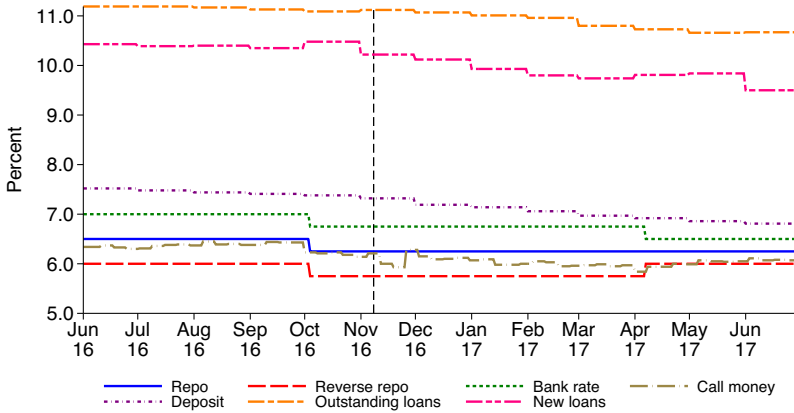


FIGURE III
Interest Rates around Demonetization

amounted to a 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 III 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, private rates also changed little. Thus, the swap between two forms of RBI liabilities occurred without a corresponding change in market interest rates. Moreover, while households deposited their cash into banks, they could freely access these funds in the form of checks, 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 specialness of cash.

III. MODEL

In this section we present a model of demonetization to generate testable cross-sectional implications and bound the aggregate impact of demonetization. Unlike mainstream models, in our

December 31, 2016, to return their old notes. Using the currency chest data described below, we find that 69% of the notes were returned by the end of November; 87% of notes were returned by December 15; and 97% of notes were returned by the end of December.

model an unanticipated fall in cash is not associated with a change in market interest rates, and we model the endogenous response of alternative forms of payment to a cash shortage, both integral features of demonetization. The environment is a closed economy composed of a continuum of identically sized regions indexed by i . The agents are households, firms, banks, and the government. Each region produces a nontraded good and a unique variety of a good ω that is traded freely across regions. We consider both perfect labor mobility and perfectly immobile labor. An important friction is downward nominal wage rigidity owing to which equilibrium employment can fall short of inelastically supplied labor.

III.A. Setup

1. *Households.* Households consume traded and nontraded goods. There are two stores of value, cash M and interest-earning deposits D . Households hold cash because of a CIA constraint along the lines of Lucas (1982), Lucas and Stokey (1987), and Svensson (1985) and because holding cash facilitates tax evasion and reduces the effective tax rate. Households in each region supply \bar{N} units of labor inelastically. They choose consumption of tradables $C_{i,t}^T$, consumption of nontradables $C_{i,t}^N$, bank deposits $D_{i,t}$, cash holdings to carry into the next period $M_{i,t}$, and financial services $f_{i,t}$ to solve:

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

subject to

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

$$(2) \quad \kappa(f_{i,t})P_{i,t}C_{i,t} \leq M_{i,t-1} + T_{i,t}^M,$$

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

where all variables except for C , f , and equilibrium labor N are nominal and denominated in the unit of account (rupees).¹⁰

10. The objective function omits an expectations operator because we only consider a perfect foresight shock.

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 noncash). Total consumption is an aggregate of traded and nontraded 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 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 $P_t^T = \left(\int_0^1 P_t^T(\omega)^{1-\sigma} d\omega \right)^{\frac{1}{1-\sigma}}$.

Equation (2) gives the CIA constraint wherein a fraction $0 < \kappa(f_{i,t}) \leq 1$ 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 . The cash share κ depends on adoption of a finance technology $f_{i,t}$. This variable encompasses a broad range of actions that households can undertake when cash is scarce, 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 accept old notes. Adopting the technology entails a utility cost (time and effort) $h(f_{i,t})$.¹¹ We assume $\kappa(0) = \bar{\kappa}$, $\kappa'(f_{i,t}) \leq 0$, $h(0) = 0$, $h'(f_{i,t}) > 0$, $h''(f_{i,t}) \geq 0$. With these assumptions, households invest in the financing technology only when the CIA constraint binds. However, the CIA constraint does not necessarily bind when $R_t > 1$ because of the tax advantage to holding cash.

2. Banks and Firms. Perfectly competitive banks take deposits and lend to firms and to the government at interest rate 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. Firms in the tradable and nontradable sectors are perfectly competitive. Each firm faces a working capital constraint where a fraction φ

11. Isomorphically, $\frac{1}{\kappa}$ has the interpretation of the within-period velocity of M . Therefore, $h(f_{i,t})$ may also include the cost of actions to increase velocity, such as spending time in lines or searching across banks to find available new notes. These costs could potentially reduce time available to engage in production, as could time spent depositing old notes, possibilities we abstract from here.

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

3. *Downward Wage Rigidity.* As in [Schmitt-Grohé and Uribe \(2016\)](#), nominal wages are downwardly rigid: $W_{i,t} \geq \gamma W_{i,t-1}$. When the constraint does not bind $N_{i,t} = \bar{N}$, yielding the complementary slackness condition $(\bar{N} - N_{i,t})(W_{i,t} - \gamma W_{i,t-1}) = 0$ when labor is immobile across regions and $(\bar{N} - N_t)(W_t - \gamma W_{t-1}) = 0$ when labor is mobile. [Kaur \(forthcoming\)](#) suggests $\gamma = 1$ in India, in which case nominal wages never fall.

4. *Government and Market Clearing.* The government prints (or destroys) money, $T_{i,t}^M = M_{i,t}^s - M_{i,t-1}^s$, issues bonds $B_{i,t}^g$, collects labor income taxes, and makes transfers to households, yielding the consolidated budget constraint:

$$\begin{aligned} & \int_0^1 (M_{i,t}^s + B_{i,t}^g + \tau(\eta_{i,t})W_{i,t}N_{i,t}) di \\ &= \int_0^1 (T_{i,t}^M + T_{i,t}^g + M_{i,t-1}^s + R_{t-1}B_{i,t-1}^g) di. \end{aligned}$$

Traded goods markets clear countrywide, $\int_i C_{i,t}^T(\omega) di = Y_t^T(\omega)$. Nontraded goods markets clear by region, $C_{i,t}^N = Y_{i,t}^N$. Furthermore, $A_{i,t}^f = B_{i,t}^f$, $A_t^g = B_t^g$, and $M_{i,t}^s = M_{i,t}$.

III.B. Demonetization

[Online Appendix](#) Section A characterizes a predemonetization steady state in which the CIA constraint does not bind due to the tax advantage of holding cash. At the start of period 0 the government (unexpectedly) announces that only a fraction of cash that households carry into period 0 is legal tender and can be used for transaction purposes and requires the remaining cash be deposited at the pre-fixed interest rate of R_{-1} . This policy forces households off their deposit Euler equation A.3. At the start of period 1, demonetization ends and the money supply returns to the level required for full employment. There is no uncertainty following the announcement of the demonetization shock.

We first give an analytical solution for a uniform demonetization across all regions and when households do not have access to

the finance technology, $\kappa'(f) = 0$. We assume a sufficiently sharp demonetization that the CIA constraint binds in period 0.¹² [Online Appendix](#) Section A contains proofs of the propositions.

PROPOSITION 1. Uniform demonetization with constant κ .

Let $Z = \frac{M_0^s}{M_{-1}} = \frac{M_0}{M_{-1}}$ where $0 < Z < 1$ so that the CIA binds and the wage constraint binds, that is, $\bar{\kappa} P_0 C_0 = M_0$ and $W_0 = \gamma W_{-1}$. If Z is sufficiently low relative to the downward rigidity of wages,¹³ $Z \cdot \frac{\eta_{-1}}{\bar{\kappa}(1+\varphi(\beta^{-1}-1))} < \gamma$, then:

i. *Output, employment decline:*

$$(4) \quad \frac{Y_0}{Y_{-1}} = \frac{N_0}{N_{-1}} = \frac{Z}{\gamma} \cdot \frac{\eta_{-1}}{\bar{\kappa}(1+\varphi(\beta^{-1}-1))},$$

ii. *Bank lending to firms declines:*

$$(5) \quad \frac{B_0^f}{P_0} = \frac{\varphi N_0}{(1+\varphi(R_{-1}-1))} < \frac{B_{-1}^f}{P_{-1}},$$

iii. *Wages and prices satisfy:*

$$(6) \quad W_0 = \gamma W_{-1}, \quad P_0^T = P_0^N = (1+\varphi(\beta^{-1}-1))\gamma W_{-1}.$$

The proportional decline between output and Z in [equation \(4\)](#) arises because of the binding CIA constraint $M_0 = \bar{\kappa} P_0 C_0$, which tightly links cash in period 0 to output $Y_0 = C_0$.¹⁴ The ratio of money holdings to labor income falls, $\eta_0 < \eta_{-1}$, owing to which

12. As long as the CIA binds, we can solve for the outcomes in period 0 without the solutions for period 1 and beyond because interest rates are pre-fixed at R_{-1} and the deposit Euler and money Euler equations are irrelevant. Verifying the conditions under which the CIA binds requires the full dynamic solution as shown in [Online Appendix](#) Section A. Due to one-sided wage rigidity, multiple values of M in period 1 induce a return to full employment. We choose the minimal such value, which 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 predemonetization level.

13. The CIA does not bind in period -1 if $\frac{\eta_{-1}}{\bar{\kappa}(1+\varphi(\beta^{-1}-1))} > 1$ (see [Online Appendix](#) Section A). Therefore, $\frac{Z}{\gamma}$ must be sufficiently less than 1. The condition does not depend only on $\frac{Z}{\gamma}$ because the nominal wage when the CIA binds is different from when the CIA does not bind.

14. Starting from the binding CIA constraint $M_0 = \bar{\kappa} P_0 C_0$, we substitute the equilibrium 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 $\eta_{-1} = \frac{M_{-1}}{W_{-1}N_{-1}}$ and $Z = \frac{M_0}{M_{-1}}$ to arrive at [equation \(4\)](#). As is clear, while in our setup P_0 is sticky downward because of the

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 exploit in our empirical work. The government reduces the supply of cash in region i in a proportion $Z_i \in (0, 1)$, that is, $M_{i,0}^s = Z_i M_{-1}^s$. We assume households cannot undo the heterogeneous distribution of cash across regions through financial markets.

PROPOSITION 2. Nonuniform demonetization with constant κ .

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

i. Regions with higher Z_i have smaller declines in output:

$$(7) \quad \frac{Y_{i,0}}{Y_{i,-1}} = \frac{Y_0^T(\omega) + Y_{i,0}^N}{Y_{i,-1}} = \frac{\alpha Z + (1 - \alpha) Z_i}{\gamma} \cdot \frac{\eta_{-1}}{\bar{\kappa}(1 + \varphi(\beta^{-1} - 1))},$$

ii. Firm borrowing falls less in regions with higher Z_i :

$$(8) \quad \frac{B_{i,0}^f}{P_0} = \frac{\varphi Y_{i,0}}{(1 + \varphi(\beta^{-1} - 1))},$$

iii. Wages and prices satisfy:

$$(9) \quad W_{i,0} = \gamma W_{-1}, \quad P_0^T = P_{i,0}^N = (1 + \varphi(\beta^{-1} - 1))\gamma W_{-1}.$$

The impact of the idiosyncratic component of the money shock is decreasing in the size of the traded sector; as $\alpha \rightarrow 1$ there is no cross-regional variation in output. Regional employment tracks regional output. Because of downward wage rigidity, the wage is equalized across regions regardless of labor mobility. Firm borrowing is increasing in Z_i . If all banks operate nationally then there is no necessary relation between local firm borrowing and loans extended by local banks. If however banks or firms face a (vanishingly) small cost to forming a cross-region lending relationship and banks have perfect internal credit markets, then there is a

downward wage rigidity, any nominal friction that keeps P_0 from falling will result in a similar expression.

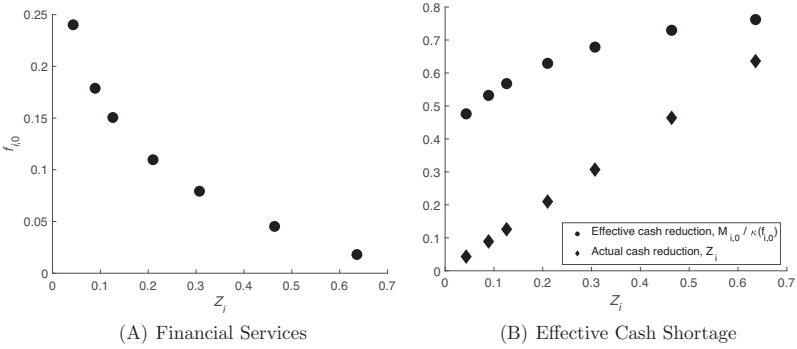


FIGURE IV

Adoption of Noncash forms of Payment

greater decline in credit creation by bank branches located in a region with a smaller Z_i .

Finally, we allow for endogenous κ . The endogenous κ breaks the unit elasticity between M and output in [equation \(4\)](#). In the absence of a closed-form solution, we provide a numerical illustration of how $f_{i,0}$ varies with Z_i .¹⁵ [Figure IV](#), Panel A shows that regions with a larger drop in cash adopt more financial services. Financial services make the effective cash shortage $\frac{Z_i}{\kappa_{i,0}}$ smaller than the measured cash shortage Z_i and, because of the selection effect, there is less heterogeneity in the effective cash shortage across regions, as depicted in [Figure IV](#), Panel B. Overall, the cross-sectional relationship between cash and output is attenuated.

To summarize, the model predicts that districts experiencing more severe demonetization will have (i) relative reductions in employment and output; (ii) faster adoption of alternative payment technologies; and (iii) lower bank credit growth. In addition, trade linkages make cross-sectional estimates a lower bound for aggregate effects.

15. The full solution requires solving for the Lagrange multiplier on the CIA constraint $\theta_{i,0}$, financing technology $f_{i,0}$, and the cash share $\eta_{i,0}$ using the three equations: $\theta_{i,0} = \frac{1}{Z_i M_{-1}} - \frac{1}{\kappa(f_{i,0})} \frac{\beta \lambda_{i,1}}{1 + \tau'(\eta_{i,0})}$, $\eta_{i,0} = \frac{Z_i(1 + \varphi(\beta^{-1} - 1))}{\alpha \mathcal{I} + (1 - \alpha) \frac{Z_i}{\kappa(f_{i,0})}}$, $\theta_{i,0} Z_i M_{-1} = -\frac{h'(f_{i,0}) \kappa(f_{i,0})}{\kappa'(f_{i,0})}$, where $\lambda_{i,1} = \frac{\eta_{i,0} - 1}{M_1(1 + \varphi(\frac{1}{\beta} - 1))}$ and $\mathcal{I} = \int \frac{Z_j}{\kappa(f_{j,0})} dj$. See [Online Appendix Section A](#) for details.

TABLE I
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
Night lights	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 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

IV. DATA AND SUMMARY STATISTICS

IV.A. 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 that partition the country. [Table I](#) summarizes the data sets used.

TABLE II
EXAMPLE CURRENCY CHEST

Date	Note	Open	Inflows			Outflows			Close
			Remit	DI	Dep	Soiled	DO	Wit	
11/15/2016	2,000	100	50	20	0	0	10	80	80
11/15/2016	1,000	800	0	0	200	600	0	0	400
11/15/2016	500	400	10	0	20	100	0	10	320

1. *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 4,000 chests spread across the country. A chest may receive newly printed notes either directly from one of the 19 RBI issue offices or from one of approximately 600 “hub” chests. Each chest 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 II 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 also define $ND = DI - DO$ as net diversions of currency received from other chests. We aggregate the chest-level data to the district level.

We define the demonetization shock in district i at date t postdemonetization, $Z_{i,t}$, as the value of nondemonetized currency in the district as of date t divided by the total value of currency in the district before demonetization. Letting $M_{i,t}^{new}$ denote the value of all new notes received in district i as of date t postdemonetization, M_i^{1000} and $M_i^{500,old}$ the value of demonetized 1,000 and 500 notes, respectively, from district i (i.e., the value of notes in chests or in circulation as of November 8), and M_i^{small} the predemonetization

value of small notes, we can express $Z_{i,t}$ as:

$$(10) \quad Z_{i,t} = \frac{M_{i,t}^{new} + M_i^{small}}{M_i^{1000} + M_i^{500,old} + M_i^{small}}.$$

We operationalize equation (10) by constructing the following variables from the currency chest data:

$$(11) \quad \text{New 2,000 notes: } M_{i,t}^{2000} = \sum_{s=\text{Oct 26, 2016}}^t \left(\text{Remit}_{i,s}^{2000} + \text{ND}_{i,s}^{2000} \right),$$

$$(12) \quad \text{New 500 notes: } M_{i,t}^{500,new} = \sum_{s=\text{Nov 9, 2016}}^t \left(\text{Remit}_{i,s}^{500} + \text{ND}_{i,s}^{500} \right),$$

$$(13) \quad \text{New small notes: } M_{i,t}^{small,new} = \sum_{s=\text{Nov 9, 2016}}^t \left(\text{Remit}_{i,s}^{small} + \text{ND}_{i,s}^{small} \right),$$

$$(14) \quad \text{All new notes: } M_{i,t}^{new} = M_{i,t}^{2000} + M_{i,t}^{500,new} + M_{i,t}^{small,new},$$

Demon. 1,000 notes:

$$(15) \quad M_i^{1000} = \sum_{s=\text{Nov 9, 2016}}^{\text{Jan 31, 2018}} \text{Soiled}_{i,s}^{1000} + \text{Close}_{i,\text{Jan 31, 2018}}^{1000},$$

$$(16) \quad \text{Demon. 500 notes: } M_i^{500,old} = \sum_{s=\text{Nov 9, 2016}}^{\text{Dec 31, 2017}} \text{Soiled}_{i,s}^{500},$$

Predemon. small notes:

$$(17) \quad M_i^{small} = \left(\frac{\sum_{s=\text{Jan 1, 2014}}^{\text{Dec 31, 2015}} (Dep_{i,s}^{small} + Wit_{i,s}^{small})}{\sum_{s=\text{Jan 1, 2014}}^{\text{Dec 31, 2015}} (Dep_{i,s}^{500} + Wit_{i,s}^{500})} \right) M_i^{500,old}.$$

Equation (11) states that we measure new 2,000 notes by summing notes received directly from RBI offices and net notes received from other chests.¹⁶ We measure new 500 notes, $M_{i,t}^{500,new}$, analogously, as well as smaller denomination (100, 50, 20, 10, and 5) notes, $M_{i,t}^{small,new}$, printed by the RBI to help meet currency demand. We measure demonetized 1,000 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 1,000 notes returned to RBI offices plus any 1,000 notes remaining in a chest as of that date, and demonetized 500 notes, $M_i^{500,old}$, by summing the value of 500 notes returned to RBI offices.¹⁷ Finally, we do not directly observe the stock of small notes before demonetization. Instead, we make the assumption that, predemonetization, all notes of denomination 500 and below flow through currency chests at the same rate and use the relative gross flows (withdrawals and deposits) and the stock of 500 notes to construct M_i^{small} as shown in equation (17). Under this assumption, the cross-district mean large-note share

16. This measure spikes temporarily when a chest receives notes from an RBI issue office that it subsequently sends to other chests. To remove these spikes, we 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 (11) to be $M_{i,t}^{2000} = \min_{t' \geq t} \sum_{p=\text{Oct 26, 2016}}^{t'} (Remit_{i,p}^{2000} + ND_{i,p}^{2000})$. We do not apply this operator to 500 notes as defined in equation (12) 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 2,000 notes.

17. 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. Although 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 1,000 and 2,000 notes, not 500 notes. A regression of $\ln Z_{i,t}$ on $\ln \left(\frac{M_{i,t}^{2000}}{M_i^{1000}} \right)$ for $t = \text{December 2016}$ yields an R^2 of 0.84. Adding $\ln \left(\frac{M_{i,t}^{500,new}}{M_i^{500,old}} \right)$ to the regression raises the R^2 only slightly to 0.88.

equals 89%, very close to the predemonetization national share of the stock of large notes reported by the RBI.¹⁸

We apply a few filters to remove districts with implausible demonetization shocks: we drop observations with $Z_{i,t} < 0$, $M_i^{500,old} \leq 0$, or where $\sum_{p=Nov\ 9,\ 2016}^t (Wit_{i,p}^{2000} - Dep_{i,p}^{2000}) < 0$ 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 nonnegative, that we observe a positive quantity of old 500 notes, that cumulative deposits of 2,000 notes by commercial banks not exceed cumulative withdrawals, and that cumulative withdrawals net of deposits (i.e., net new 2,000 notes actually received by commercial banks) not differ from arrivals of new 2,000 notes by too much.¹⁹ Applying these criteria removes 47 of 589 districts, which collectively contain less than 3% of demonetized currency.

2. Employment. We obtain data on employment status from Consumer Pyramids starting in January 2016. Unlike countries such as the United States, India does not have a governmental monthly household survey or a monthly survey of establishments.²⁰ 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

18. We use the currency flow rate of 500 notes because of the possibility that some 1,000 notes were used for storage and therefore did not flow through chests at the same rate as other notes. Nonetheless, using the average flow of 500 and 1,000 notes yields an alternative $Z_{i,t}$ with a correlation of 0.999 with the measure defined in the text. We also considered two other alternatives: (i) allocating the national quantity of small notes as reported in [RBI \(2017a\)](#) using the shares of soiled small notes from each district during 2014 and 2015; and (ii) assuming all districts have the same share of large notes of 0.87 as reported by the RBI for the national economy. [Online Appendix](#) Table B.2 reproduces our main results using these alternative measures and shows that our main findings remain unchanged.

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

20. 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 noncoverage of the demonetization period or of informal-sector employment make these data inappropriate for our analysis.

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 their 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 age 15+) per month, comparable to the sample size (although not the coverage rate) of the CPS.²¹

We construct district-month measures of employment and population by aggregating the individual observations using the survey weights. This step introduces four complications. First, although 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 because responses in that month mix predemonetization and postdemonetization outcomes. Third, the survey weights do not aggregate to estimates of district population that 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.

3. *Night Lights.* Our second measure of real activity following demonetization is the change in night light intensity. Night light intensity refers to low-light imaging data collected by satellite and filtered to measure the quantity of artificial (i.e.,

21. The survey shares other similarities with the CPS and the Survey of Income and Program Participation, such as the use of a stratified 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 and Nicobar Islands, Dadra and Nagar Haveli, Lakshadweep, and Daman and Diu.

human-generated) light in an area. Such data have been used to augment official measures of output and output growth and generate estimates for areas or periods where official data are unavailable (Henderson, Storeygard, and Weil 2012). In our context, night light intensity could reflect shops closing early because of a lack of customers or lower activity in factories that usually operate after dark.

We use the VIIRS DNB data collected by NOAA using the Suomi National Polar Partnership satellite, which was launched in 2011 (Elvidge et al. 2017). Despite the filtering, some stray light remain in these data. NOAA provides annual composites which contain additional processing to remove such stray light. We follow World Bank (2017) in removing cells (roughly 0.5 km²) for which the annual average of the data differ substantially from the annual composites and then 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 night lights 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) postdemonetization.

4. *ATM/POS*. We obtain monthly data for the period January 2016 to June 2017 on the value of ATM withdrawals and 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 that enables payment by credit or debit card over a phone 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.

5. *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 prepaid cards.²²

6. *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.

7. *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. For all three variables we use data from 2015, the last year of data available. We obtain national quarterly seasonally adjusted nominal and real GDP from the OECD.²³

IV.B. Summary Statistics

Table III reports cross-district summary statistics for December 2016, March 2017, and June 2017. The median district in December 2016 had currency equal to 42% of its predemonetization level. Essentially all districts experienced a contraction, with the 90th percentile district at 70% of its predemonetization level. At the other extreme, the 10th percentile district had currency equal to only 33% of its predemonetization level. By March 2017, currency in the median district had recovered to 83% of its predemonetization level and by June 2017 the median district had no net contraction remaining. 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.

22. 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."

23. The Indian Ministry of Statistics does not publish a seasonally adjusted measure of quarterly GDP.

TABLE III
SUMMARY STATISTICS

	Mean	Std. dev.	P10	P50	P90	Count
December 2016						
Demonetization shock	0.45	0.23	0.22	0.42	0.70	542
Predemon. large-note share	0.89	0.04	0.83	0.89	0.95	542
Night lights (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	535
Bank credit (log change)	-0.01	0.04	-0.04	-0.01	0.02	535
2015 GDP per capita (Mi)	0.10	0.08	0.04	0.09	0.18	540
2015 agriculture share of GDP	0.16	0.12	0.03	0.14	0.34	532
Population per sq. km (Th)	1.24	8.70	0.16	0.47	1.45	539
March 2017						
Demonetization shock	0.90	0.42	0.48	0.83	1.36	550
Predemon. large-note share	0.89	0.04	0.83	0.89	0.95	550
Night lights (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	543
Bank credit (log change)	0.06	0.05	0.02	0.07	0.11	543
June 2017						
Demonetization shock	1.23	0.60	0.61	1.11	1.95	548
Predemon. large-note share	0.89	0.04	0.83	0.89	0.95	548
Night lights (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	541
Bank credit (log change)	0.08	0.06	0.02	0.08	0.12	541

IV.C. 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-differences estimation.

As a starting point, the demonetization shock $Z_{i,t}$ could vary across districts because of variation in the predemonetization

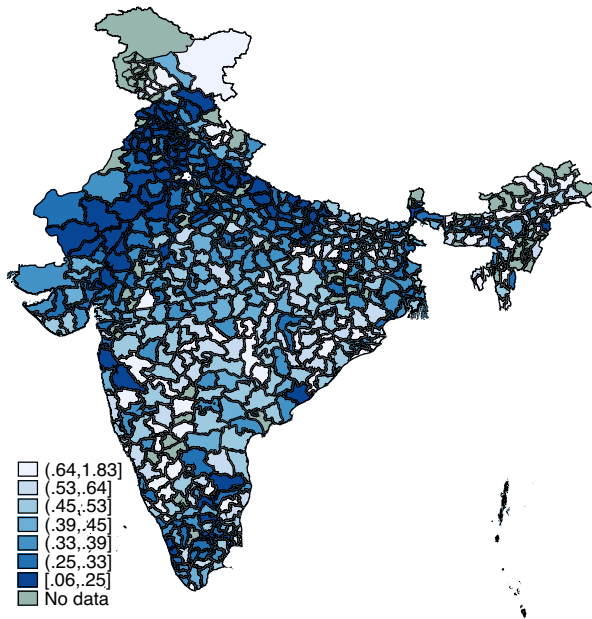


FIGURE V
Demonetization Shock by District

share of large notes or because of variation in the arrival rate of new notes. In fact, Table III shows that the predemonetization share of large notes varies little across districts, with a standard deviation of 4 percentage points and an interdecile range of 83% to 95%. As a result, essentially all of the variation in $Z_{i,t}$ comes from variation in the replacement rate of demonetized notes; the correlation of $Z_{i,t}$ and an alternative measure that sets the large-note share to the national level of 0.87 reported by the RBI is above 0.99.

Figure V shows a map of the demonetization shock in December 2016 by district, with districts with larger shocks shaded darker. The RBI offices in some states appear to have received more new currency notes than in others. We address the spatial correlation in what follows by clustering standard errors by state.

A violation of parallel trends could occur if the RBI steered new notes toward areas with secularly growing or shrinking currency demand. However, 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 postmortem of the episode contained in the RBI's 2017 annual report (RBI 2017a, 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 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 knew of the policy ahead of time. Moreover, in October 2016 the RBI could not have known the precise geographic distribution of existing 500 and 1,000 notes in circulation. The next sentence of the report indicates that the RBI did not begin to incorporate real-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 that 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 pretrends in the data. Here we report in Table IV 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, population density, and demonetized notes per capita. The largest bivariate correlation is with demonetized 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. In what follows we report specifications that control directly for GDP per capita, agriculture's share of GDP, and population density.

TABLE IV
WHAT IS THE CURRENCY SHOCK CORRELATED WITH?

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Log GDP per capita	-0.21 (0.15)						0.02 (0.22)
Agriculture's share of GDP		0.00 (0.07)					-0.13 ⁺ (0.07)
Log distance to closest RBI office			0.13* (0.06)				-0.11 (0.06)
Log bank branches per capita				-0.21 (0.12)			-0.12 (0.17)
Log population density					-0.32** (0.10)		-0.39** (0.12)
Log demonetized notes per capita						-0.33** (0.08)	-0.32** (0.09)
BM df	13.0	9.8	19.7	18.6	16.9	13.9	
R^2	0.04	0.00	0.02	0.04	0.10	0.11	0.22
Clusters	31	31	33	31	31	31	31
Observations	540	532	542	540	539	540	531

Notes. The table reports the correlation coefficient (columns (1)–(6)) and partial correlation coefficient (column (7)) with $z_{i,t}$, the log of the demonetization shock. Standard errors in parentheses are clustered by state using the bias-reduction modification suggested by [Imbens and Kolesár \(2016\)](#). The row gives the associated t -distribution degrees of freedom for the coefficient. **, *, + denote significance at the 1%, 5%, or 10% level, respectively.

V. CROSS-SECTIONAL RESULTS

We now 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 night lights, fell in these areas relative to areas experiencing 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, together provide a consistent account of the effects of demonetization.

We emphasize at the outset three important advantages of the cross-sectional approach. First, it holds constant other policies or shocks affecting the whole economy around the period of demonetization. Moreover, even if other policies or shocks had differential effects across subnational areas, the cross-sectional approach will uncover the causal effect of demonetization as long as the demonetization shock is uncorrelated with the geographic

footprint of 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 sample with varying treatment intensity. The large sample makes possible tighter inference. Third, the cross-sectional comparison isolates the component of demonetization due to the temporary unavailability of currency. Although we believe this aspect to have been the dominant channel, in the next section we discuss other possible channels that might apply at the aggregate level.

V.A. Cross-Sectional Specification

Our empirical specification is:

$$(18) \quad (y_{i,t} - y_{i,baseline}) = \beta_{0,t} + \beta_{1,t}z_{i,treatment} + \Gamma_t X_i + \epsilon_{i,t},$$

where $y_{i,t}$ denotes the natural log of an outcome variable in district i , $y_{i,baseline}$ denotes the log of the variable in the period immediately preceding demonetization (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 $t \in \{\text{November 2016, December 2016}\}$ 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 (18). 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 $z_{i,t}$ that 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 of the possible concern raised above that the distribution of new notes after December 2016 reflected contemporaneous factors and because in any case the stability of the rank of a district in the cross-sectional distribution of shocks over time yields too little variation to separately identify contemporaneous from lagged effects.²⁴ Second, some of the dependent variables used in the analysis have wide tails. The log-log specification helps reduce sensitivity to outliers.

24. For example, the Spearman rank correlation of z_i for December 2016 and March 2017 is 0.80.

We further trim observations with dependent variable in 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 V. This level of clustering results in about 30 clusters.²⁵ 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).²⁶ Imbens and 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.

V.B. Results

1. *ATM Withdrawals.* Figure VI and Table V show our first result—areas that 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 (10). Each blue circle (color version available online) 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 30 quantile bins of $z_{i,t}$. Thus, the figure overlays a “binned scatter plot” on top of the raw data. The dashed red line shows the best-fit line.

25. India consists of 29 states and 7 union territories, and we use the term “state” 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 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 that follow have a maximum of 33 clusters. In specifications controlling for 2015 GDP per capita, we further drop the two union territories of Daman and Diu and Lakshadweep due to a lack of GDP data.

26. The LZ2 correction applies a small-sample adjustment that 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.

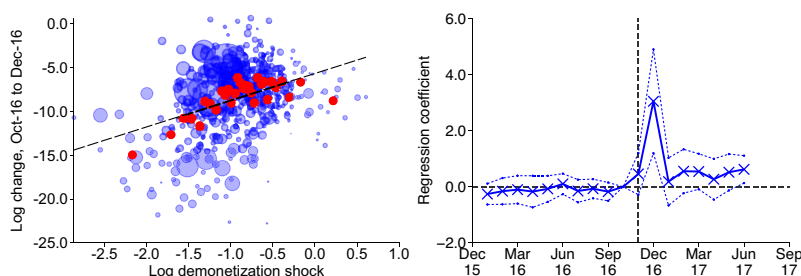


FIGURE VI
ATM Withdrawals

The left panel presents a scatter plot of the log change in ATM withdrawals between October 2016 and December 2016 and the log demonetization shock. The light blue circles show the raw data and are sized proportional to 2015 district GDP. The dark red circles average observations into 30 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 \(18\)](#) for the period indicated on the horizontal axis.

The right panel of [Figure VI](#) reports the coefficient from estimating [equation \(18\)](#) 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.

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 V](#) demonstrates the robustness of the cross-sectional pattern. Column (1) reproduces the slope coefficient from the left

TABLE V
ATM WITHDRAWALS

	(1)	(2)	(3)
Demonetization shock	3.04** (0.85)	2.86** (0.92)	3.08* (1.12)
Log GDP per capita		0.04 (0.85)	0.17 (0.76)
Agriculture's share of GDP		0.02 (0.03)	-0.01 (0.03)
Log population density		-0.39 (0.43)	-0.04 (0.29)
Control lagged outcomes	No	Yes	Yes
Weight	No	No	Yes
Fitted 90-10 differential	35.3	33.2	35.8
Treatment BM df	12.8	14.6	12.8
R^2	0.13	0.18	0.17
Clusters	33	31	31
Observations	531	521	521

Notes. The dependent variable is the log point change from October 2016 to December 2016 multiplied by 10. Columns (2) and (3) also control for nine lags of the dependent variable. Column (3) weights the regression by district GDP. Standard errors in parentheses are clustered by state using the "LZ2" bias-reduction modification suggested by [Imbens and Kolesár \(2016\)](#). ** and * denote significance at the 1% or 5% level based on a t -distribution with degrees of freedom for the demonetization shock shown in the row "Treatment BM df."

panel of [Figure VI](#). Column (2) adds covariates to the regression: 2015 GDP per capita, the 2015 share of agriculture in GDP, log population density, and nine lags of ATM transactions growth. The lags of ATM growth control directly for any pretrends, while the 2015 level of GDP per capita and agriculture's share of GDP control for basic features of the industrial structure of Indian districts. As shown in [Table IV](#), population density correlates with the demonetization shock. Yet inclusion of these covariates has little effect on the coefficient on $z_{i,t}$.

Column (3) weights the regression by district GDP. The coefficient changes little. 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 ([Solon, Haider, and Wooldridge 2015](#)). 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. [Online Appendix Section B.D](#) further explores heterogeneous treatment effects by interacting $z_{i,t}$ with other variables and shows

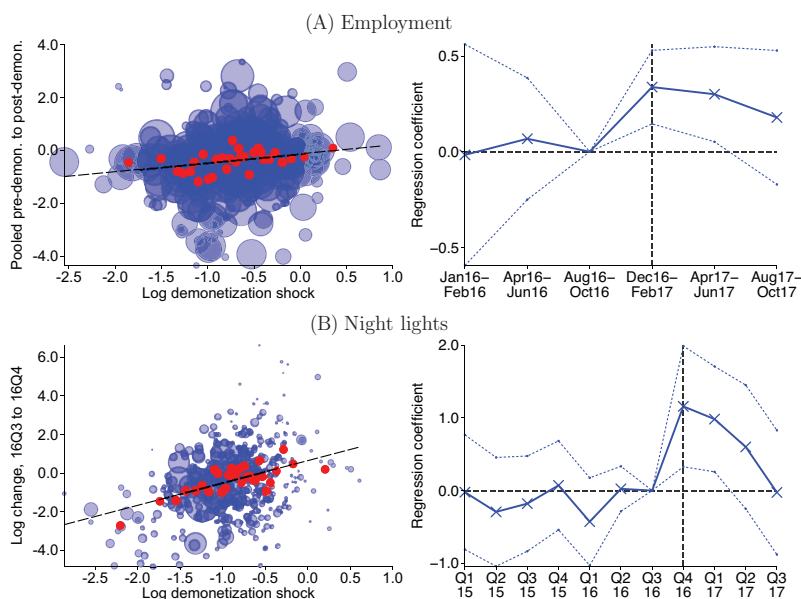


FIGURE VII
Real Activity

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 demonetization 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 night light activity between July to September 2016 and November–December 2016 and the log demonetization shock. The light blue circles show the raw data and are sized proportional to 2015 district GDP. The dark red circles average observations into 30 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 \(18\)](#) for the period indicated on the horizontal axis.

economically small and statistically insignificant interaction coefficients.

V.C. Employment and Night Lights

[Figure VII](#) and [Table VI](#) display our next main result—demonetization reduced real economic activity. The scatter plots in the left panels of [Figure VII](#) show nonparametrically that areas with larger declines in currency experienced sharper declines in employment and in night light activity after demonetization occurred. The right panels show no evidence of pretrends and

TABLE VI
REAL ACTIVITY

Dep. var.: log change in	Employment			Night lights			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Demonetization shock	0.34** (0.09)	0.47** (0.08)	0.22 (0.16)	1.20** (0.37)	1.15** (0.34)	1.44* (0.46)	1.19** (0.31)
Log GDP per capita		0.22+ (0.11)	0.04 (0.25)		-0.25 (0.20)	0.22 (0.30)	
Agriculture's share of GDP		0.00 (0.00)	0.00 (0.00)		0.01 (0.01)	-0.00 (0.01)	
Lop population density		0.11+ (0.05)	0.03 (0.07)		0.03 (0.10)	-0.18 (0.23)	
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	4.0	5.6	2.6	14.0	13.3	16.7	13.9
Treatment BM df	9.9	11.4	12.3	11.4	13.7	9.5	12.8
R^2	0.03	0.30	0.21	0.11	0.50	0.49	0.10
Clusters	22	22	22	32	30	30	33
Observations	407	396	396	473	464	464	537

Notes. The dependent variable is the log point change from predemonetization to postdemonetization 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), and (6) also 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 are clustered by state using the “LZ2” bias-reduction modification suggested by [Imbens and Kolesár \(2016\)](#). **, *, + denote significance at the 1%, 5%, or 10% level based on a t -distribution with degrees of freedom for the demonetization shock shown in the row “Treatment BM df.”

highly statistically significant postdemonetization differences, which last into spring 2017 before fully dissipating as all areas get remonetized.²⁷

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 4.0 log points, while the predicted difference in night

27. 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 VI](#) pools observations from December 2016, January 2017, and February 2017 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.

light growth is 14.0 log points.²⁸ 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 night light growth of 0.3. Their estimate remains similar even for a subsample of low- and middle-income countries. Using this elasticity yields a predicted difference in GDP of roughly 4.2 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 night light activity—yet they suggest quantitatively similar declines in output. The two measures together provide powerful evidence of a link between money and output during demonetization.²⁹

The remainder of [Table VI](#) illustrates the robustness of the employment and night light results. Columns (2) and (5) show robustness to controlling for lagged outcomes and the level of GDP per capita and agriculture's 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 employment for districts with fewer individual observations. Finally, our baseline

28. Technically, the predicted difference in the growth rate of the employment-to-population ratio is 4.0 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 4.0 log point difference given in the main text.

29. [Online Appendix](#) Table B.1 shows that the night light response reflects differential patterns of electricity consumption. Quarterly data on electricity consumption by district do not exist. Instead, we use state-level data on electricity consumption and show (i) the cross-district relationship between night light growth in 2016Q4 and demonetization severity also holds at the state level; (ii) there is a strong cross-state relationship between night light growth and growth of electricity consumption; and (iii) after controlling for electricity consumption, there is no relationship between night light growth and demonetization severity. This last result is exactly what should happen if night light growth is related to demonetization only because electricity consumption is related to demonetization.

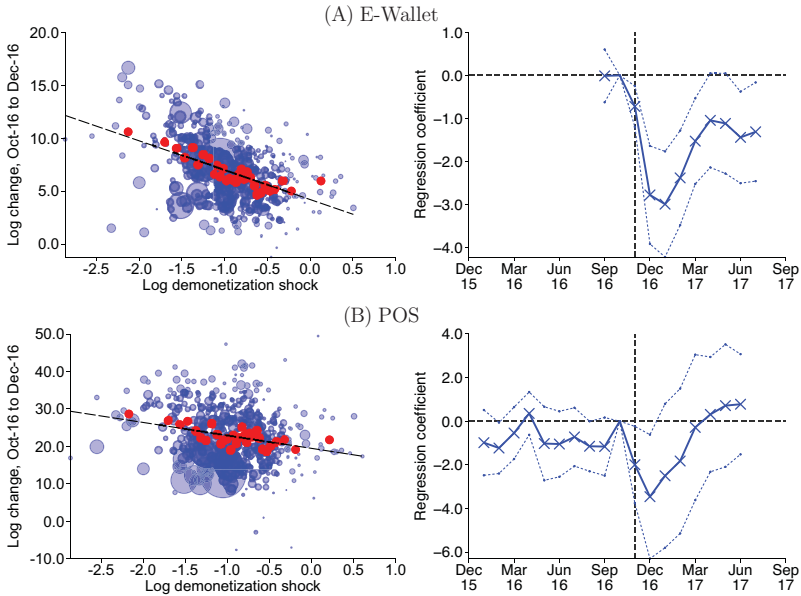


FIGURE VIII

Alternative Forms of Payment

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 demonetization shock. The light blue circles show the raw data and are sized proportional to 2015 district GDP. The dark red circles average observations into 30 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 \(18\)](#) for the period indicated on the horizontal axis.

sample for night light activity only excludes districts in the state of Uttar Pradesh because they exhibit implausible growth of human-generated night lights between 2016Q4 and 2017Q1. Column (7) shows that including these districts has essentially no effect on the estimated effect on night light activity in 2016Q4.³⁰

1. *POS and E-Wallet.* The next set of results in [Figure VIII](#) and [Table VII](#) show the shift to alternative payment

30. 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 night lights in 2017Q1 is that Uttar Pradesh held statewide elections in February and March 2017, and the ruling party accelerated electrification in the run-up to the election.

TABLE VII
ALTERNATIVE FORMS OF PAYMENT, DEC-16

Dep. var.: log change in	E-wallet			POS		
	(1)	(2)	(3)	(4)	(5)	(6)
Demonetization shock	-2.78** (0.53)	-2.99** (0.47)	-3.41** (0.69)	-3.46* (1.31)	-4.24** (1.38)	-3.50+ (1.71)
Log GDP per capita		-0.74 (0.57)	-0.41 (0.50)		-2.57** (0.80)	-3.23** (0.72)
Agriculture's share of GDP		0.01 (0.02)	0.02 (0.02)		0.14** (0.02)	0.19** (0.03)
Log population density		0.12 (0.32)	0.14 (0.23)		-1.53* (0.55)	-1.16 (0.90)
Control lagged outcomes	No	Yes	Yes	No	Yes	Yes
Weight	No	No	Yes	No	No	Yes
Fitted 90-10 differential	-32.2	-34.7	-39.6	-40.2	-49.3	-40.6
Treatment BM df	13.0	13.3	11.6	12.3	13.9	9.8
R ²	0.20	0.24	0.23	0.05	0.31	0.40
Clusters	30	29	29	33	31	31
Observations	512	503	503	522	499	499

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

technologies. Payments using both e-wallet and POS increased more in districts experiencing sharper declines in money following demonetization. Thus, although these areas experienced declines in overall economic activity and ATM usage, they had faster growth of alternative payment mechanisms. This pattern strongly militates against the presence of an unobserved demand shock confounding our identification, as a pure demand shock would induce positive comovement across all payment mechanisms and output. Although the e-wallet data start only in September 2016, limiting our ability to test for pretrends, the POS data show no differential adoption during the predemonetization period.

[Table VII](#) shows robustness to the usual specification perturbations. The e-wallet results are highly robust and are all statistically significant. The standard errors in the POS regressions are much larger, such that the coefficient on $z_{i,t}$ is significant only at the 10% level in the weighted specification.

2. *Deposits and Credit.* [Figure IX](#) and [Table VIII](#) report our final set of results covering bank deposit and credit growth. We

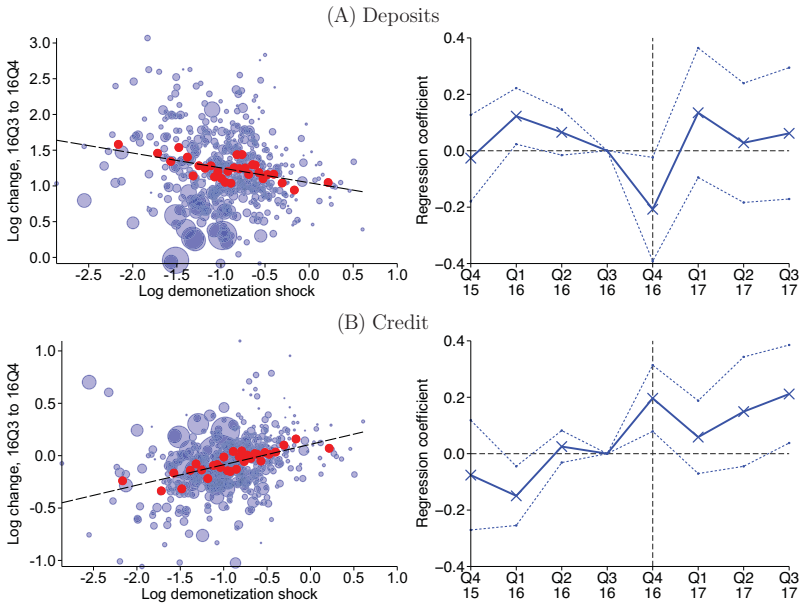


FIGURE IX

Bank Deposits and Credit

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 demonetization shock. The light blue circles show the raw data and are sized proportional to 2015 district GDP. The dark red circles average observations into 30 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 \(18\)](#) for the period indicated on the horizontal axis.

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.

TABLE VIII
BANK DEPOSITS AND CREDIT, 2016Q4

Dep. var.: log change in	Deposits			Credit		
	(1)	(2)	(3)	(4)	(5)	(6)
Demonetization shock	-0.21* (0.09)	-0.35** (0.10)	-0.30* (0.11)	0.20** (0.05)	0.14** (0.04)	0.09+ (0.05)
Log GDP per capita		-0.25** (0.06)	-0.28** (0.05)		-0.00 (0.03)	0.07+ (0.04)
Agriculture's share of GDP		0.01** (0.00)	0.01** (0.00)		-0.00** (0.00)	-0.00* (0.00)
Log population density		-0.10+ (0.05)	-0.15** (0.04)		-0.06* (0.02)	-0.01 (0.03)
Control lagged outcomes	No	Yes	Yes	No	Yes	Yes
Weight	No	No	Yes	No	No	Yes
Fitted 90-10 differential	-2.4	-4.0	-3.5	2.3	1.6	1.1
Treatment BM df	12.9	13.9	10.4	13.2	14.9	11.7
R ²	0.04	0.29	0.43	0.11	0.25	0.24
Clusters	32	30	30	32	30	30
Observations	531	521	521	531	520	520

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

VI. DISCUSSION AND RELATION TO AGGREGATE IMPACT

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. These cross-sectional patterns reject monetary neutrality and the cashless limit in the context of India’s demonetization.

We now turn to the effect on aggregate economic activity. We first report time series aggregates around demonetization. Then we discuss how the cross-sectional evidence is informative about the aggregate impact of demonetization.

VI.A. Aggregate Time Series

Figure X plots time series aggregates around demonetization. The vertical line in each panel shows the period in which demonetization occurred. In interpreting these figures, it is important to keep in mind that other economic shocks and policies

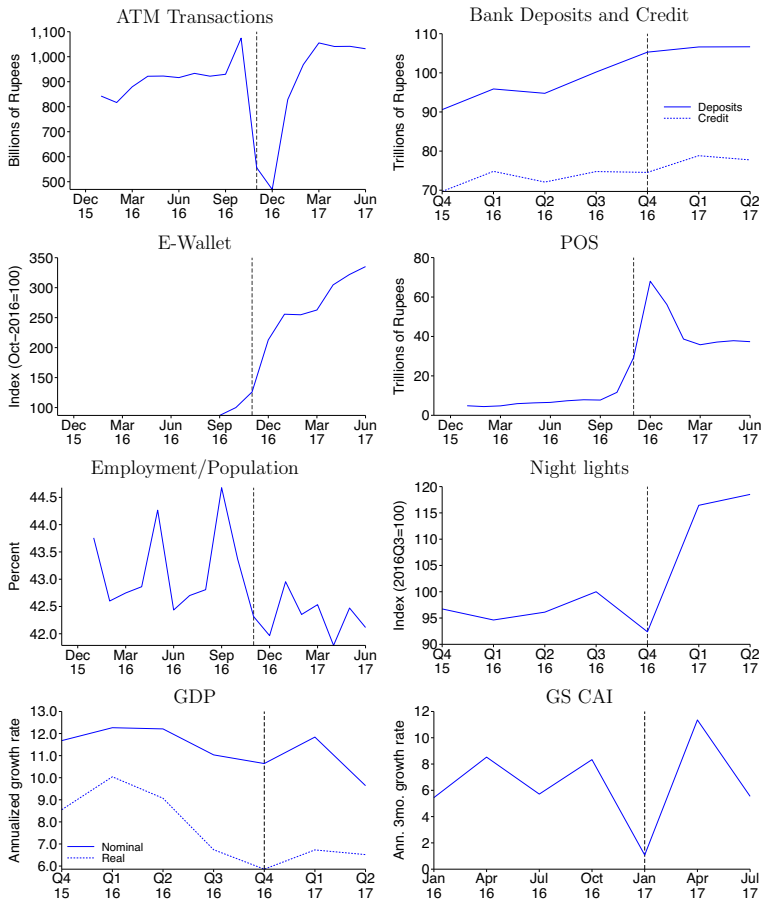


FIGURE X
Aggregate Time Series

The dashed lines denote the month or quarter in which demonetization occurred. The upper six panels show time series based on aggregating our district-level data. The bottom left panel shows the seasonally adjusted growth rate of GDP from the OECD. The bottom right panel shows the annualized three-month growth rate of the Goldman Sachs Current Activity Indicator for India ([Goldman Sachs 2018](#), © 2019 Goldman Sachs Global Investment Research. All rights reserved.).

besides demonetization also affected the global economy and India specifically during this period, factors that the cross-sectional approach could ignore. Salient examples include the election of Donald Trump 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 nonrepatriable accounts and accompanying exchange rate volatility in November 2016, and an overhaul of the Indian sales tax collection system in summer 2017.

These caveats aside, aggregate ATM withdrawals, e-wallet use, and POS payment transactions all 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.³¹

In contrast, aggregate GDP growth, employment, and night lights do not exhibit clear patterns around demonetization, and neither do bank deposits or credit.³² The apparent insensitivity of GDP could reflect offsetting shocks at the aggregate level. As well, and importantly, although the level of GDP includes an estimate of informal sector activity derived from a quinquennial survey, quarterly changes in GDP do not reflect any direct measurement of informal sector activity. Instead, output of the informal sector in nonsurvey years is projected forward based on other, mostly formal-sector indicators.³³ The informal sector in India is

31. Because the wallet company provided data only in index format, the e-wallet panel of [Figure X](#) shows an unweighted average across districts.

32. 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.

33. The level of output of the informal sector in the base year is obtained from the quinquennial National Sample Survey of Unincorporated Enterprises. The survey in use at the time of writing was conducted in 2010–2011. For manufacturing, the projection indicator is the growth of formal-sector manufacturing as measured in the Annual Survey of Industries (when it becomes available) or the index of industrial production. For services, the indicators are growth rates of sales taxes and service taxes, which reflect a combination of changes in compliance and real activity ([CSO 2015](#)). Thus, even annual GDP does not incorporate direct measures of informal-sector activity. In addition, quarterly GDP relies on a subset of the source data to allocate annual GDP across quarters. These indicators, such as the monthly industrial production index, mostly cover the largest formal sector establishments. As an additional complication, India does not report seasonally adjusted quarterly GDP. The data in [Figure X](#) come from the OECD.

estimated to account for 81% of total employment (ILO 2018) and 44% of total output (CSO 2018) and is especially cash-intensive and therefore likely to have been affected by demonetization. Indeed, if demonetization pushed some activity from the informal to the formal sector, official GDP could have spuriously risen. The government itself, in the annual report written by the chief economist of the Government of India (CEA 2017, 19), also concluded that official GDP would understate the impact of demonetization: “Recorded GDP growth in the second half of FY2017 will understate the overall impact [of demonetization] because the most affected parts of the economy—informal and cash-based—are either not captured in the national income accounts or to the extent they are, their measurement is based on formal-sector indicators. For example, informal manufacturing is proxied by the Index of Industrial Production, which includes mostly large establishments. So, on the production or supply side, the effect on economic activity will be underestimated.”

Employment and night light activity better reflect the informal sector but have distinct drawbacks at the aggregate level. For employment, the short time series of the data precludes seasonal adjustment. For night light activity, changes in long-run factors such as electric capacity and measurement error in the procedure for removing stray light can generate changes in night light activity unrelated to high-frequency economic activity. Importantly, as long as district-specific seasonal patterns in employment and the long-run and measurement error components of night light activity growth are orthogonal to the demonetization shock $z_{i,t}$, the cross-sectional approach above remains valid despite these challenges (see Online Appendix Section B.B for additional detail). These considerations favor emphasis on the impact of demonetization as revealed by the cross-sectional patterns.

The lower right panel of Figure X reports an alternative measure of aggregate activity, the Goldman Sachs Current Activity Indicator (CAI) for India (Goldman Sachs 2018).³⁴ The CAI combines 25 high-frequency indicators, including measures of informal-sector and rural activity such as energy consumption (diesel consumption, petrol consumption, and power demand) and two-wheeler and tractor sales along with high-frequency measures of formal-sector activity, such as purchasing manager

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indices. The CAI shows a much sharper decline in economic activity than does official GDP, and of a magnitude more consistent with the aggregate implications of the cross-section, discussed next.

VI.B. Aggregate Implications of the Cross-Section

To assess the implications of the cross-sectional patterns for the aggregate impact of demonetization, we start by cumulating the cross-sectional effects over districts. This calculation uses 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, that is, $Z_{i,t} = 1$, and then sums over districts. The calculation would exactly recover the national impact of the currency shortfall if each district were an isolated entity. The formula for the cumulated effect in month t is:

$$(19) \quad \frac{\sum_{i:Z_{i,t} \leq 1} (e^{\beta_{1,t} Z_{i,t}} - 1) Y_{i,baseline}}{\sum_i Y_{i,baseline}} \approx \frac{\beta_{1,t} \sum_{i:Z_{i,t} \leq 1} Z_{i,t} Y_{i,baseline}}{\sum_i Y_{i,baseline}},$$

where $Y_{i,baseline}$ denotes the level of the variable in the pre-demonetization period. Intuitively, the cumulated decline is approximated by the regression coefficient multiplied by a pretreatment outcome-weighted average of the demonetization shock. Using the coefficients shown in Table VI, columns (1) and (4), for employment this calculation yields a decline of 3.3 percentage points, while for night lights this calculation yields a decline of 12.0 percentage points, which translates into an output decline of 3.6 percentage points after applying the 0.3 elasticity advocated by Henderson, Storeygard, and Weil (2012). Online Appendix Figure B.3 shows the counterfactual paths of employment and night light activity implied by these totals.

The preceding calculation assumes a log-linear relationship between the cash shortage and outcome variables. Although the scatter plots appear consistent with such linearity, we lack the power to test for a nonlinearity or kink at small declines in cash because essentially all districts experienced a large decline in currency. Assuming instead a flat relationship (no effect of the cash shortage on outcomes) for cash declines of less than 10% would

change the implied decline in employment to 3.0 percentage points and the decline in night lights to 10.9 percentage points.³⁵

The next step is to relate the quantity defined in [equation \(19\)](#) to the actual national effect of demonetization. Two types of considerations arise. First, the impact of the currency shortage found in the cross-section may differ from the impact in the aggregate. In the context of the model in [Section III](#), trade linkages across districts make the cumulated decline in output a lower bound for the true aggregate decline. The lower bound arises because of the tradables 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 \(2019\)](#) 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. Moreover, the model accommodates arbitrary labor mobility without affecting the lower-bound result because the downward wage constraint binds in all areas. More generally, higher labor mobility at the local than the national level, which can make cross-sectional multipliers larger than the aggregate ([Chodorow-Reich 2019](#)), cannot undo the lower bound in this case because our empirical labor market measure—the employment-to-population ratio—already removes the component of the employment change due to labor mobility.³⁶

Applying the lower-bound result to the cross-sectional estimates for employment and night lights, we conclude that the cash shortage caused by demonetization generated a decline in national economic activity of roughly 3 percentage points or more in November and December 2016 relative to a no-demonetization counterfactual.³⁷ Similarly, the effect on credit implies a

35. Alternatively, we can adjust the district-level shocks by the fraction of demonetized notes that had been used for storage by assuming constant chest velocity of notes not used for storage. Doing so implies slightly smaller but still statistically significant aggregated declines in employment and night light activity.

36. More precisely, the cumulation of the employment results imposes a fixed population. If in reality some workers moved from more-demonetized to less-demonetized regions, then the number in the text would understate the employment decline.

37. The aggregated changes in ATM withdrawals, e-wallet transactions, and POS transactions from applying [equation \(19\)](#) are also all smaller than the actual

2 percentage points or more decline in 2016Q4. These effects dissipate over a few months. Is such a decline large? The magnitude of the peak effect on output is 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 rejects 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 preexisting CIA constraint.

The second consideration in relating the cumulated cross-sectional results to the aggregate involves effects of demonetization beyond the decline in currency. For example, demonetization may have bolstered or curtailed confidence in the government or caused short-run supply disruptions as economic activity migrated from the informal to the formal sector. Our evidence speaks to the effect of the cash shortage caused by demonetization on cross-sectional and aggregate outcomes; it is not informative about other possible channels that apply only at the aggregate level or are orthogonal to the cash replacement shock. Abstracting from these other channels, the lower-bound result for the impact of the cash shortage points to an absolute decline in economic activity at the end of 2016 not captured in official statistics.³⁸

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.

38. 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% (2% annualized) in 2016Q4 from the previous quarter. This follows from the 3% decline in November and December and no impact in the predemonetization month of October.

VII. CONCLUSION

Using geographic variation in the severity of demonetization, we have shown that a sharp, temporary decline in currency caused declines in ATM withdrawals, reduced economic activity, faster adoption of alternative payment technologies, and higher deposit and lower bank credit growth in Indian districts. These cross-sectional patterns reject monetary neutrality and the cashless limit in this episode.

Although certainly exotic, demonetization offers lessons for other settings. For example, what economic costs would result from a country abandoning the euro and having to print new national currency? Or, in a country like Sweden that already largely uses electronic payment media, what would happen if the national payments network were to suffer an outage? Our results point to the possibility of substantial economic disruption in these events.

Finally, we focused 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. 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 noncash 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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SUPPLEMENTARY MATERIAL

An [Online Appendix](#) for this article can be found at *The Quarterly Journal of Economics* online. Data and code replicating tables and figures in this article can be found in [Chodorow-Reich et al. \(2019\)](#), in the Harvard Dataverse, [doi:10.7910/DVN/NN42EE](https://doi.org/10.7910/DVN/NN42EE).

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