

Shocks and Technology Adoption: Evidence from Electronic Payment Systems *

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Abstract

Using a dynamic technology choice model, we study the diffusion of technologies subject to positive adoption externalities. Building on this theoretical framework, we examine how the adoption of electronic payment technologies in India was affected by the 2016 demonetization. The analyses provide several results that are consistent with the model. On the one hand, the shock – which caused a large but temporary reduction in cash – led to a persistent increase in the adoption of electronic payment. On the other hand, however, the response also exhibited substantial state-dependence: high adoption responses occurred in areas where adoption externalities prior to the shock were likely to be stronger. Thus, the presence of externality in adoption – while it allows temporary interventions to have large, persistent effects – may potentially exacerbate initial differences. Lastly, we also provide evidence on how the adoption wave may have helped offsetting the real effects of the cash crunch.

Keywords: Externalities, Technology Diffusion, Fintech, Demonetization.

JEL Classification: O33, E51, E65

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1 Introduction

A crucial component of the link from innovation to growth is the diffusion of new technologies (Hall and Khan, 2003). The adoption of new technologies by firms is often a slow process, encumbered by many potential barriers (Rosenberg, 1972). The empirical literature offers several examples of firms failing to use efficiency-enhancing technologies (Mansfield, 1961) or processes (Bloom et al., 2013), for reasons ranging from the presence of organizational frictions (Atkin et al., 2017), to slow social learning (Munshi, 2004; Conley and Udry, 2010; Gupta et al., 2019), to lack of financial development (Comin and Nanda, 2019; Bircan and De Haas, 2019).

For technologies characterized by positive externalities — that is, when the benefits of adoption increase as the use of the technology becomes more widespread — coordination problems can be a key obstacle to diffusion. Individual firms may expect either high or low adoption rates by other firms. Consistent with these expectations, they may either adopt or reject the technology, giving rise to multiple possible equilibria.¹ In these situations, understanding how firms may coordinate on technology adoption, or fail to do so, is an important question, for both research and policy.

In this paper, we study the extent to which large economic shocks (or policy interventions) can help resolve these coordination problems and accelerate the pace of technology diffusion. We analyze a simple dynamic technology-adoption model where, because of positive externalities, firms’ adoption decisions are complements. Using a novel empirical setting, we show that – consistent with the model – a *temporary* aggregate shock can lead to a *persistent* wave of technology adoption. However, we also show that responses to the shock exhibit strong state-dependence. Large adoption waves only occur when pre-shock externalities are large; otherwise, adoption shifts are only as persistent as the shock itself. Thus, our results show that while large, temporary shocks can lead to persistent changes in the *average* pace of technology diffusion, they can also exacerbate *differences* in adoption in the long run.

Our analysis focuses on a particular technology: electronic payment systems. Electronic payment systems are a perfect example of technology exhibiting externalities (Katz and Shapiro, 1994; Rysman, 2007), and therefore the coordination problem may be an important obstacle to adoption (Crowe et al., 2010). In this context, externalities may arise in different ways. The network nature of this technology is likely the main force to generate complementarity across firms in the decision to opt into the platform. Intuitively, the more firms join the platform, the more valuable the electronic payment system will be for customers. In turn, this

¹Technologies characterized by externalities are very common, in particular in the new economy, where many products are network-based or structured as multi sided markets. In their classic work, Katz and Shapiro (1985) discuss several sources of externalities. In particular, they highlight how externalities can arise both directly – in situations where the number of users affects the quality of the product – or indirectly – where the number of users affect the value of other add-on products (e.g. hardware/software) or the type of postpurchase services (e.g. car). Furthermore, for very new products, externalities can also arise from learning about the quality of the products and understanding its costs and benefits (Suri, 2011).

effect will increase the demand for electronic payments and therefore enhance the value of using the new technology for a marginal firm. However, alternative mechanisms — for instance, learning about the benefit of the technology (Munshi, 2003) — could also generate externalities in this context. In general, the key takeaways of the paper will not depend on the specific source of externalities, making our results broadly applicable to different contexts.

The setting for our analysis is the Indian demonetization of 2016. On November 8th, 2016, the Indian Government announced that it would void the two largest denominations of currency in circulation and replace them with new bills. At the time of the announcement, the voided bills accounted for 86.4% of the total cash in circulation. The public was not given advance warning, and the bills were voided effective immediately. A two-month deadline was announced for exchanging the old bills for new currency. In order to do so, old bills had to be deposited in the banking sector. However, withdrawal limits, combined with frictions in the creation and distribution of the new bills, meant that immediate cash withdrawal was constrained. As a result, cash in circulation fell and bank deposits spiked. Cash transactions became harder to conclude, but more funds were available for use in electronic payments. Importantly, this shock was very large in size but temporary. In first approximation, things improved dramatically during the month of January and the situation normalized starting in February.²

We first show that the demonetization led to a large increase in the use of electronic payment systems. We focus primarily on data from the largest Indian provider of non-debit-card electronic payments. This payment platform operates as a digital wallet. The digital wallet consists of a mobile app that allows consumers to pay at stores using funds deposited in their bank accounts. Payment is then transferred to merchants' bank accounts via the app.³ In aggregate, the overall activity in the platform roughly doubled in size several times during the two months following the announcement. Additionally, we show that adoption was *persistent*, though the shock was not. In aggregate, there was no significant mean-reversion in adoption or transaction volumes once cash withdrawal constraints were lifted. Aggregate adoption effects are also visible in the use of debit card payment terminals, but appear much weaker for credit card payments and are mostly driven by the intensive margin. Overall, the aggregate data thus suggest that the shock led to a wave of adoption of electronic payments.

In order to shed light on the role of externalities in the transmission of this shock to adoption decisions, we start by analyzing a dynamic technology-adoption model. Our model is based on the framework of

²In the paper, we show that cash in circulation restarted to grow vigorously with the new year and we highlight how the Government removed all limitations by the end of January. Furthermore, the evidence from Google Search trends data confirms the timing.

³The costs associated with the adoption of this technology for merchants are small; there are no usage fees, and all that is required to join the platform is to have a bank account and a mobile phone, both of which had high ownership rates in India by 2016 (Agarwal et al., 2017). Nevertheless, in what follows, we discuss the role of fixed costs, and argue that they are unlikely to give a full account of the transmission of the shock to adoption.

Burdzy et al. (2001). Firms face a choice between two technologies under which to operate, one of which is subject to positive externalities — the flow profits from operating under this technology increase with its rate of use by firms overall. Moreover, the relative benefit of adopting the technology with externalities is subject to aggregate shocks.⁴ We show that in response to a large, *temporary* shock to the relative value of the two technologies, the total number of users increases *persistently*. Moreover, a distinctive implication of externalities is that the number of *new* users joining the platform remains higher than in the pre-period, even after the shock has receded.⁵ This reflects the fact that, with externalities, the initial increase in adoption triggered by the shock increases the relative value of adoption for other firms; this “snowball” effect can thus generate endogenous persistence in the response of adoption.

Aside from the persistent rise in new users, a key implication of the model is that adoption responses exhibit state-dependence. Specifically, the adoption response to a given shock depends positively on the level of adoption prior to the shock. When the initial adoption rate is low, a large shock may temporarily raise adoption. However, once the shock is undone, the adoption rate will tend to converge back to its initially low level. By contrast, when the initial adoption rate is sufficiently high, the same transitory shock may lead to full and permanent adoption. In the model, the initial adoption rates fully capture the initial strength of externalities in adoption; the key prediction is thus that the pre-shock strength of externalities determines the “tipping point” beyond which the transitory shock can generate endogenous persistence in adoption.

We then turn to the electronic data in order to carefully document the dynamics of adoption of electronic wallet technologies by firms during the Indian demonetization. As a first step, we estimate the causal impact of the cash contraction on adoption activity at the district level. This panel analysis allows us to overcome some of the limitations of the aggregate event study, in particular when looking outside the immediate reaction to the shock. We show that variation across districts in the importance of chest banks — local branches in charge of the distribution of new bills (currency chests) — can be exploited to identify heterogeneity in the exposure to the shock at the local level. Using this design, we show that the districts more exposed to the demonetization experienced a larger and more persistent increase in adoption following the demonetization, consistent with the predictions of the model. Additionally, higher exposure also predicts a bigger increase in the number of new firms joining the platform, and this is true even after the cash crunch has receded and restrictions on cash withdrawals have been lifted. In light of the theoretical model, this latter

⁴The presence of these common shocks helps eliminate the potential equilibrium multiplicity arising from complementarities in adoption decisions. The model is closely related to the literature on global games and equilibrium selection (Carlsson and Van Damme, 1993; Morris and Shin, 1998, 2003). This literature has also analyzed the effects aggregate (public) signals in environment where agents’ actions are complements (Morris and Shin, 2002). The two key differences of the framework we study is with global games models is that (a) firms have no private information on the returns to adoption; (b) firms solve a dynamic coordination problem, instead of a one-shot, static model. The latter difference is important, as it allows us to distinguish between short- and long-run effects of the shock. See Burdzy et al. (2001) for a more detailed discussion of the relationship of this framework with the global games literature.

⁵We show, in particular, that this prediction would not obtain if the main barrier to adoption were fixed costs.

result can only be rationalized in the context of a model where complementarities in adoption are important. The paper also carefully discusses several tests that support the causal interpretation of these results.

Next, we test the model’s predictions regarding state-dependence in the data, and we find strong support for them. As a first step, we provide evidence in line with state-dependence at the *district level*. We show that districts with larger initial adoption responded relatively more, in line with the model’s predictions. Furthermore, we test whether the rise in adoption during the demonetization period was stronger in areas that were located closer to those districts that already had a very high adoption level before the shock (*hubs*). The idea behind this test is that being located close to these electronic payment hubs increases the strength of externalities prior to the shock, since customers are more likely to travel across closely located districts. Building on this intuition, we exploit within-state variation in distance, and we show that the increase in adoption is larger in closer districts.

Then, we provide *firm-level* evidence on state-dependence. Using a specification derived from the analysis of the model, and similarly to [Munshi \(2004\)](#) and [Goolsbee and Klenow \(2002\)](#), we estimate how the intensity of adoption by other firms in the same zipcode and business area affects the adoption decision at the firm level.⁶ Overall, we find that adoption by neighboring firms in the same industry has a strong, positive effect on the usage of the technology. In line with the prediction of the model, this effect is particularly larger during the shock period, when firms transition to the new technology. Importantly, these results do not simply capture variation across locations and industries, since they hold when we augment the analysis with a wide set of zip code by time and industry by time fixed-effects.

The evidence of state-dependence in adoption is not only important from a positive standpoint; it also has implications for understanding whether, and how, large policy interventions have the potential to shape technology choices. Indeed, our model shows that the particular form of state-dependence that we highlight disappears when interventions are sufficiently persistent. That is, sufficiently persistent interventions will trigger full adoption regardless of initial conditions. This highlights a potential trade-off: on the one hand, very persistent interventions may be costly or distortionary; on the other, very temporary interventions will tend to generate state-dependent responses, and thus accentuate initial differences in adoption.

We explore the quantitative importance of this trade-off, and of complementarities in adoption more generally, in section 5. We estimate the model of section 3 via simulated method of moments, using the data on adoption rates in Indian districts following the demonetization. Our key parameter of interest is the size of adoption externalities. Following the intuition described above, we show that this parameter can be identified using the difference between short- and long-run adoption rates following the shock. Our estimation strongly

⁶The analysis is conducted at the pincode level, which is a geographical unit in India similar to a 5-digit zip code in the US. Section 4 provides more details on pincodes in India.

rejects the null that there are no adoption externalities. Moreover, we use the estimated model to construct a counterfactual path of average adoption rates across districts in the absence of externalities. We find that externalities accounted for approximately 60% of the total response of adoption to the demonetization shock. We also use the model to study how the economy would have responded if the features of the cash crunch had been different. We show that adoption would have been substantially lower (between 50% and 80%) if the shock had been smaller or if the cash swap had been executed according to plan, suggesting that some of the unintended features of the cash crunch led to higher adoption. However, we also show that, keeping the present value of the decline in cash constant (and equal to its model-implied value), a cash crunch with a smaller initial magnitude (by around 40%) but a longer half-life (by a factor of 2), would have led to higher long-run adoption rates (by about 10%) and lower dispersion in adoption across districts in adoption rates in the long-run. Consistent with the discussion above, this shows that more persistent interventions can lead to lower state-dependence in the response of adoption.

To conclude, we show that — while electronic payments did not allow consumers to completely offset the effects of the cash crunch — their presence has helped households to limit the negative impact of the shock. Using novel household data, combined with the chest bank exposure measure described above, we show that total consumption contracted relatively more in more exposed districts. In particular, a standard-deviation increase in the exposure to the shock corresponds to an almost 4% larger decline in consumption. This contraction was completely temporary and larger in the subset of the consumption basket that is more likely to be unnecessary. However, we find that districts that were characterized by a large penetration of traditional electronic money saw a much smaller decline in consumption.

1.1 Contribution to the literature

Our paper contributes to the existing literature in three areas. First, our results contribute to the work studying the process of diffusion of technologies across firms. The literature has provided evidence on a number of potential barriers to technology diffusion. [Atkin et al. \(2017\)](#) suggest that the presence of organizational frictions may prevent adoption of cost-reducing technologies. At the same time, several papers highlight the role of social learning in technology adoption, in particular in the agricultural context (e.g. [Conley and Udry \(2010\)](#); [Munshi \(2004\)](#); [Gupta et al. \(2019\)](#)). Lastly, using cross-country data, [Comin and Nanda \(2019\)](#) emphasize the role of financial development in fostering technological diffusion.⁷

Our results provide novel evidence on the importance of coordination frictions in technology adoption. We show that complementarities played an important role in adoption following the Indian demonetization shock. More broadly, our results shed light on the role that policy might play in incentivizing technology

⁷For a complete review of the literature on technology adoption, see [Foster and Rosenzweig \(2010\)](#).

adoption in the face of coordination problems. They suggest that large, temporary policy shocks — such as transitory taxes or subsidies on the use of particular technologies — may be sufficient to permanently shift adoption equilibria toward more desirable outcomes, at least when externalities in adoption are present.⁸ However, the paper also highlights the possible welfare costs in terms of inequality of adoption that these temporary interventions may have. The importance of complementarity for understanding the propagation of payment technologies is also consistent with the contemporaneous paper by [Higgins \(2019\)](#), which explores how a policy-induced permanent increase in debit cards in Mexico affected both the consumption behavior of adopters and the suppliers’ response.

Second, our paper also contributes to the growing literature of fintech. Despite the importance of payment technologies in this industry ([Rysman and Schuh, 2017](#)), a large part of the literature in this area has focused on the impact of fintech in funding markets, either for households or firms ([Buchak et al., 2018](#); [Tang, 2018](#); [Fuster et al., 2018](#); [de Roure et al., 2018](#); [Howell et al., 2018](#)). In this area, the paper has two main contributions. First, the paper provides a general framework for understanding how adoption of fintech technologies can be affected by policy shocks. While the model can easily be applied to technologies outside the fintech sphere, the data application suits particularly well this industry, where new products are usually characterized by low adoption costs and strong externalities in adoption. This analysis highlights how coordination problems may be an important constraint to the expansion of electronic payments, even when adoption costs are essentially zero. In these situations, temporary policy interventions by governments or companies can foster adoption. However, our analysis also shows that the response to this type of interventions may be highly heterogeneous and the level of inequality in adoption may actually rise in response to this shift. Second, this work also provides direct evidence of how fintech can add value by lowering adoption costs in the financial service industry. Consistent with this idea, higher cost options – like more traditional electronic payments – did not expand much at the extensive margin during the demonetization. This increase in financial access is particularly important given the electronic payment’s benefits documented in the literature (e.g. [Yermack \(2018\)](#), [Suri and Jack \(2016\)](#), [Jack and Suri \(2014\)](#), [Beck et al. \(2018\)](#)).⁹

Lastly, our paper also contributes to the understanding of the impact of the demonetization on the Indian economy. On the one hand, our paper show that the large policy shock had some important positive effects by causing a persistent increase in the adoption of new payment technologies. Along this dimension,

⁸In this area, this paper contributes to the empirical evidence on network externalities. Among others, [Björkegren \(2015\)](#) quantifies the impact of externalities in determining the cost of a tax on network goods; [Saloner et al. \(1995\)](#) examines the important of the potential size of a network in the decision to adopt a new technology (ATM machine); [Tucker \(2008\)](#) study how different types of adopters may influence the expansion of the network; [Ryan and Tucker \(2012\)](#) studies the adoption of video calling by firms in a dynamic setting.

⁹This discussion is also particularly relevant given recent debate on the costs of cash and cash alternatives in modern economies ([Rogoff, 2017](#)).

the work closest to us is [Agarwal et al. \(2018\)](#) which – leveraging mostly on time-series variation around the demonetization – documents a general shift to electronic payments. Relative to this work, our paper provides novel cross-sectional evidence on the way the propagation of this technology happened during the demonetization period. This evidence allows us to provide a better characterization of adoption dynamics highlighting the importance of state-dependence. Furthermore, our paper shows that complementarity in adoption was a key feature of the technology in explaining the aggregate shift. On the other hand, our paper also documents the negative effects of this policy, in the form of a reduction of consumption by households in response to the scarcity of cash in the local markets. These results are consistent with the effects on Indian output estimated by the contemporaneous paper by [Chodorow-Reich et al. \(2018\)](#). While our paper differs greatly in its main focus, our household-level analysis also significantly extends the understanding of the real effect of the shock by providing evidence on the heterogeneity of the effects across different consumption groups and areas. Furthermore, our evidence on the importance of local penetration of electronic payments for understanding the heterogeneity in response also provides direct evidence of the role played by electronic payments in limiting the impact of the shock.

The rest of the paper is organized as follows. Section 2 provides some background on the demonetization and documents aggregate adoption effects. Section 3 analyzes our simple model of technology adoption and derives key predictions. Section 4 tests these predictions in the electronic wallet data. Section 5 documents consumption responses to the shock, and section 6 concludes.

2 Background

2.1 The demonetization

On November 8, 2016, at 08:15 pm IST, Indian Prime Minister Narendra Modi announced the demonetization of Rs.500 and Rs.1,000 notes, during an unexpected live television interview. The announcement was accompanied by a press release from the Reserve Bank of India (RBI), which stipulated that the two notes would cease to be legal tender in all transactions at midnight on the same day. The voided notes were the largest denominations at the time, and together they accounted for 86.4% of the total value of currency in circulation. The RBI also specified that the two notes should be deposited with banks before December 30, 2016. Two new bank notes, of Rs.500 and Rs.2,000, respectively, were to be printed and distributed to the public through the banking system. The policy’s stated goal was to identify individuals holding large amounts of “black money,” and remove fake bills from circulation.¹⁰

¹⁰In its annual report for 2017-2018, the RBI reported that 99.3% of the value of voided notes had been deposited in the banking system during the demonetization.

However, the swap between the new and old currency did not occur at once: instead, the public was unable to withdraw cash at the same rate as it was depositing old notes. As a result, the amount of currency in circulation dropped precipitously during the first two months of the demonetization period. This can be seen in Figure 2, which plots the monthly growth rate of currency in circulation.¹¹ Overall, cash in circulation declined by almost 50% during November and continued declining in December.

Partly, this cash crunch reflected limits on cash withdrawals put in place by the RBI in order to manage the transition.¹² But the cash crunch also reflected the difficult logistics of the swap itself. In order to ensure that the policy remained undisclosed prior to its implementation, the RBI had not printed and circulated large amounts of new notes to banks. This caused many banks to be unable to meet public demand for cash, even under the withdrawal limits. The public rushed to obtain the available cash, resulting in long waiting lines at banks.¹³

Importantly, the demonetization did not lead to a reduction in the total money supply, defined as the sum of cash and bank deposits. The total money supply was stable over this period, as reported in Figure 2. In its press release, the RBI highlighted that deposits to bank accounts could be freely used through “various electronic modes of transfer.” The public was thus still allowed to transact using any form of noncash payment, such as cards, cheques, or any other electronic payment method; cash transactions were the only ones to be specifically impaired.¹⁴

Despite its magnitude, the cash crunch was a temporary phenomenon. Overall, things significantly improved in January and essentially normalized in February. The cash in circulation grew significantly again in January 2017, suggesting that the public was able to withdraw cash from banks (see Figure 2). Furthermore, by January 30th, 2017, the Government lifted most of the remaining limitations on cash withdrawals, in particular removing any ATM withdrawal limit from current accounts.¹⁵ Consistent with the brief disruption period, the general perception of the negative consequences of the demonetization on

¹¹The time series for currency in circulation reported in this graph does not mechanically drop with the voiding of the two notes; it only declines as these notes are deposited in the banking sector.

¹²In its initial press release, the RBI indicated that over the counter cash exchanges could not exceed Rs.4,000 per person per day, while withdrawals from accounts were capped at Rs.20,000 per week, and ATM withdrawals were capped at Rs.4,000 per day per card, for the days following the announcement. Additionally, a wide set of exceptions were granted, including for fuel pumps, toll payments, government hospitals, and wedding expenditures. Banerjee et al. (2018) discuss the uncertainty surrounding the withdrawal limits and exceptions, and argue that this uncertainty may have exacerbated the overall confusion during this transition period.

¹³In a survey of 214 households in 28 slums in the city of Mumbai, 88% of households reported waiting for more than 1 hour for ATM or bank services between 11/09/2016 and 11/18/2016. In the same survey, 25% of households reported waiting for more than 4 hours (Krishnan, 2017). Another randomized survey conducted over nine districts in India by a mainstream newspaper, Economic Times, showed that the number of visits to either a bank or an ATM increased from an average of 5.8 in the month before demonetization to 14.4 in the month after demonetization (<https://economictimes.indiatimes.com/news/politics-and-nation/how-delhi-lost-a-working-day-to-demonetisation/articleshow/56041967.cms>).

¹⁴See Chodorow-Reich et al. (2018) for a discussion of the RBI’s liabilities, and of key policy and market rates, during the demonetization period.

¹⁵Overall, limits started to be progressively relaxed after the announcement. After January, a limit on withdrawal from saving account was still present (raised in February 2017 to Rs.50,000 per week). However, by mid-March 2017, all limits on withdrawals had been removed.

payment systems significantly improved with the new year (see Figure D.1).¹⁶

The demonetization thus had three key features relevant to our analysis. First, it led to a significant contraction of cash in circulation. Second, it did not change the total money stock, that is, the sum of cash and deposits. As a result, the public could still access and use money electronically once the notes had been deposited. Third, it was short-lived: the cash shortage was particularly acute in November and December, but quickly normalized with the new year.

2.2 The adoption of electronic payment technologies

Overall, the demonetization was associated with a large uptake in electronic payments. We start by illustrating this fact using data from one of the leading digital-wallet companies in the country. The company allows individuals and businesses to undertake transactions with each other using only their mobile phone. To use the service, a customer would normally need to download an application and link their bank account to the application. However, in 2016 the company also established a new service that allowed customers to make payments without the need of internet or a smart phone. Merchants can then use a uniquely assigned QR code to accept payments directly from the customers into a mobile wallet.¹⁷ The contents of the mobile wallet can then be transferred to the merchant’s bank account.

Figure 3 reports data for the total number and total value of transactions executed by merchants using this technology around the week in which the demonetization was implemented.¹⁸ In the months before the shock, the weekly growth in the usage of the wallet technology had been positive on average but relatively modest. However, in the weeks following the demonetization the shift towards this payment method was dramatic. In particular, in the week after the demonetization the number of transactions grew by more than 150%, while the value of transactions increased by almost 200%. Furthermore, for the whole month after the shock, weekly growth rates were consistently around 100%.

One important observation is that this initial positive effect of the demonetization upon adoption did not dissipate with time, even when the cash-availability constraints were relaxed. In other words, this evidence

¹⁶Figure D.1 reports the monthly plot (09/2016 to 07/2017) of Google Searches for several key words that could be associated with the shock. Data are obtained by Google Trends, and the index is normalized by Google to be 0 to 100, with the value of 100 assigned to the day with the maximum number of searches made on that topic. Across all the panels, we find that Google searches connected to the demonetization spiked in November, remained high in December, but then significantly dropped in January before returning to the pre-shock levels in February. One exception is the search on “ATM Cash withdrawal limit today” which reached its maximum on January 31, 2017. This is consistent with the fact that January 31, 2017 was the date when most limits on ATM withdrawals were lifted by the RBI.

¹⁷To be more specific, there are multiple ways to transact using the digital wallet. First, customers can scan the merchants’ unique QR code in the application installed on their smartphones to complete the transaction. Second, instead of scanning the QR code, customers can enter the mobile number of the merchant. In this case, the merchant would receive a unique code from the company, which is then used by the customer to complete the transaction. Third, if a smartphone or mobile internet are not available, customers can call a toll-free number and ask the wallet company to make a transaction using the cell-phone number of the merchant. To use this feature, customers needed to be enrolled through a one-time verification process.

¹⁸We describe and analyze the disaggregated data underlying these graphs in detail in section 4.

suggests that a temporary shift in the availability of cash led to a permanent increase in the usage of the platform. In particular, the data suggest a slow-down in aggregate growth starting in January, which is when the limits on the circulation of new cash started to be relaxed. However, after a small negative adjustment in early February, the average growth rate over the next two months remained on average small but positive, confirming that users did not abandon the platform as cash became widely available again.¹⁹

The data shared with us by the electronic wallet company end in June 2017. However, it is important to point out that the increase in electronic-wallet technologies in India also persisted after this period. According to the official estimates by the Reserve Bank of India,²⁰ mobile-wallet transactions increased from 75 million to over 300 million between September 2016 and March 2017, which is the central period in our analysis. In the most recent data report (March 2019), transactions total to around 385 million per month. Therefore, if anything, electronic-wallet technologies kept growing at a relatively high rate also after the initial increase induced by the shock.

Aside from this fintech platform, more traditional electronic payment technologies were also available to the public. To explore traditional electronic payment methods, we collect publicly available data on monthly debit- and credit-card activity aggregated at the national level by the RBI.²¹ Figure 4 presents these data. In particular, the first panel reports the growth in the number of transactions for both credit and debit cards, across ATMs and points of sale (stores). In the second panel we report the growth in the number of cards, again divided across debit and credit cards.

Two findings are important to highlight. First, the permanent increase in electronic payments is not unique to electronic-wallet technologies. In particular, the number of transactions at point of sales increased dramatically in both November and December, before returning in January to levels similar to the pre-shock period. This evidence suggests that the demonetization also led to a permanent increase in debit-card transactions. Second, the short-run increase is completely driven by the intensive margin, unlike with the electronic wallet. In other words, the overall volume in debit-card transactions increased only because debit-card holders started to use them more frequently. In particular, in the second panel of Figure 4, we document a small growth in new cards during either November and December.

To understand the differences between traditional and fintech electronic payments, it is now worth highlighting their differences. Relative to cards, adoption costs for wallets are much lower. This is especially true for merchants, since the electronic wallet can be accessed almost instantaneously, with nothing more than a

¹⁹We believe that this decline may be also related to the announcement of a small fee in February and an increase in competition and entrance by other electronic payment companies.

²⁰These data are available in the payment section of the RBI data warehouse.

²¹We obtain these data from: <https://rbi.org.in/scripts/atmview.aspx>, which reports monthly data at the bank level on the number of debit cards and credit cards outstanding; the number and amount of transactions made using each system; and the source of transactions (at the ATM or point of sale).

phone and a bank account. Furthermore, for small and medium-sized merchants — who make up the bulk of our data — this technology does not entail any direct monetary cost.²² The higher adoption costs of cards for merchants are consistent with some of the empirical patterns reported in Figure 4. In particular, this feature explains why the response on the extensive margin – e.g. increase in new cards or point of sales – has been extremely limited for traditional payments.²³

Overall, the aggregate data on both electronic wallets and debit or credit cards indicate that the monetization was associated with a large take-up in electronic payment systems. Moreover, the use of these payment systems by merchants persisted beyond the period of the cash crunch. Consistent with the view that credit and debit cards are subject to larger adoption and usage costs for merchants than electronic wallets, adoption effects for these technologies are more muted than for the electronic wallet, which will be the main focus of the rest of our analysis.

3 Theory

In this section, we analyze a simple model of technology adoption. The model nests two mechanisms that could account for the adoption wave documented in the previous section. The first is the existence of externalities across firms in the use of the new technology. The second is the presence of fixed costs associated with switching from the old to the new technology. Additionally, the model is fully dynamic. The model is a variant of Frankel and Pauzner (2000) and Burdzy et al. (2001), in which firms face fixed costs of adjusting the technology under which they operate.

The purpose of the model is twofold. First, it allows us to general testable predictions regarding the characteristics of adoption dynamics in the presence of externalities. Second, it allows us to analyze the role of shock persistence, and in particular how it interacts with externalities to generate state-dependence in adoption.

3.1 Model

Economic environment Time is discrete: $t = 0, \Delta, 2\Delta, \dots$. There is a collection of infinitely-lived firms, indexed by $i \in [0, 1]$, that are risk-neutral and discount the future at rate e^{-r} ; we call this group of firms a “district”, by analogy with our empirical setting in the following sections. At different points in time, firm

²²Merchants using the digital wallet are classified by the provider into three segments: small, medium and large. Small merchants have lower limits on the amount they can transact and pay 0% transaction costs. Medium merchants can transfer money to their bank account at midnight every day up to a certain limit. Large merchants can transact any amount but pay a percentage of the transfer amount as a fees. Our data only cover small and medium merchants.

²³In this dimension, our setting is very different from Higgins (2019), which instead studies a technology — debit cards — which still requires, for merchants, a large set-up cost as well as regular fees.

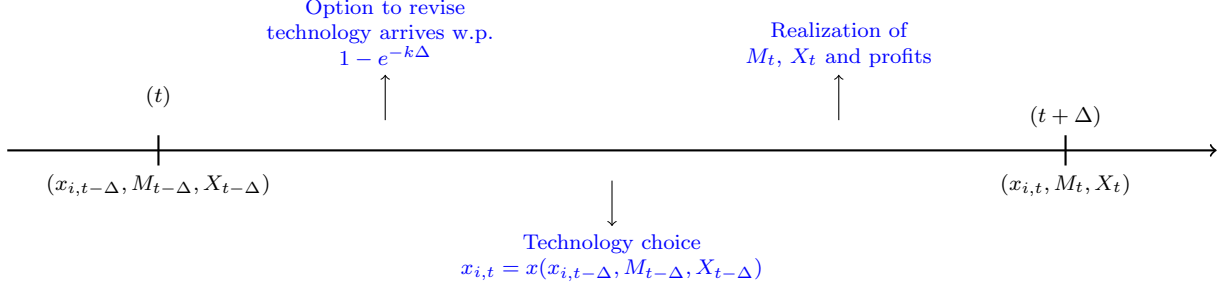


Figure 1: Timing of actions and events during a period.

i must choose between operating under one of two technologies, $x_{i,t} \in \{c, e\}$, where c stands for “cash” and e stands for “electronic money,” or “e-money,” for short. Flow profits of the firm depend on the technology it uses; we assume that they are given by:

$$\Pi(x_{i,t}, M_t, X_t) = \begin{cases} M_t & \text{if } x_{i,t} = c, \\ M^e + CX_t & \text{if } x_{i,t} = e, \end{cases}$$

where:

$$M^e > 0, \quad C \geq 0, \quad \text{and} \quad X_t \equiv \int_{i \in [0,1]} \mathbf{1}\{x_{i,t} = e\} di. \quad (1)$$

This assumption says that flow profits to technology e are increasing in the number of other firms in the district also using e . The parameter $\frac{\partial \Pi}{\partial X_t} = C > 0$ controls the strength of this effect. The assumption that $C > 0$, that is, the presence of increasing external returns to e , is what will generate complementarities in the decision to adopt e .

On the other hand, flow profits to technology c are exogenous and subject to shocks. These shocks are common to all firms in the district. For simplicity, we refer to M_t as “cash,” though it may be thought of as capturing, more broadly, cash-based demand in the district. We assume that cash follows an AR(1) process:

$$M_t = (1 - e^{-\theta\Delta})M^c + e^{-\theta\Delta}M_{t-\Delta} + \sqrt{\Delta}\sigma\epsilon_t, \quad \epsilon_t \sim N(0, 1), \text{ i.i.d.} \quad (2)$$

where M^c is the long-run mean of M_t , σ is the standard deviation of innovations to M_t , and the parameter θ captures the speed of the mean-reversion of the shock.

There are two frictions that might prevent switching between technologies. First, during each increment of time Δ , a mass $1 - e^{-k\Delta} \in [0, 1]$ of firms is able to revise their technology choice. This “technology adjustment” shock is purely idiosyncratic, and in particular, it arrives independently of the common shock. When $k \rightarrow +\infty$, firms can continuously adjust their technology choices, while when $k = 0$, they are permanently

locked into their initial choice. We will assume $0 < k < +\infty$, that is, sluggish adjustment.

Second, there are fixed (pecuniary) costs of adopting technology e . Specifically, a firm must pay a fixed cost κ if it decides to revise its technology from cash to electronic payments. There is no cost of switching from electronic payments to cash and no cost of staying with the same technology.

It is important to highlight the key distinctions between these two frictions. While both modeling assumptions represent a constraint against changing the technology, the two features are conceptually very different. In particular, the presence of a sluggish adjustment simply implies that firms are not always at their optimum. This assumption could be justified by behavioral or rational frictions that prevent firms to re-optimize their operation at every point in time. However, this assumption does not add any constraint on the relative costs of adoption between the two technologies. For instance, you could still have sluggish adjustments ($0 < k < +\infty$) – for instance because the management re-optimize a firm's operation only infrequently – even when electronic payments and cash are characterized by zero fixed-cost of adoption ($\kappa = 0$). When we discuss about the fixed cost of adopting electronic payment, we are going to implicitly refer to $\kappa =$, because this is the parameter that captures specifically the cost of the adopting a new technology (electronic payment) relative to the status-quo (cash).

The timing of actions within period t is depicted in Figure 1. Note that firms make their technology choice at the beginning of period t , before either the money stock M_t or the current fraction of adopters X_t are determined. Their information set at the moment of making the technology choice is thus only $\{x_{i,t-\Delta}, M_{t-\Delta}, X_{t-\Delta}\}$.

Technology choice Let $V(x_{i,t}, M_{t-\Delta}, X_{t-\Delta})$ be the value of a firm *after* any potential technology revisions, and define:

$$B(M_{t-\Delta}, X_{t-\Delta}) = V(e, M_{t-\Delta}, X_{t-\Delta}) - V(c, M_{t-\Delta}, X_{t-\Delta}).$$

This is relative value of having technology e in place. Appendix B shows that it follows:

$$B(M_{t-\Delta}, X_{t-\Delta}) = \mathbb{E}_{t-\Delta} \left[(\Pi_t^e - \Pi_t^c) \Delta + e^{-(r+k)\Delta} B(M_t, X_t) + e^{-r\Delta} (1 - e^{-k\Delta}) g(B(M_t, X_t)) \right] \quad (3)$$

where $\Pi_t^e = \Pi(e, M_t, X_t)$, $\Pi_t^c = \Pi(c, M_t, X_t)$, and $g(B) = \max(0, \min(B, \kappa))$. When there are no fixed costs of switching, $\kappa = 0$, we have $g(B) = 0$. In this case, $B(.,.)$ is simply the expected present value of $\Pi_t^e - \Pi_t^c$, the difference in cash flows from switching from cash to electronic money. With fixed costs, $g(B) \geq 0$; in that case, $g(B)$ captures the relative value of already having technology e , for a firm which receives the technology adjustment shock.

The technology adoption rule for adjusting firms is given by:

$$x(x_{i,t-\Delta}, B_{t-\Delta}) = \begin{cases} c & \text{if } B_{t-\Delta} \leq 0 \\ x_{i,t-\Delta} & \text{if } B_{t-\Delta} \in [0, \kappa] \\ e & \text{if } B_{t-\Delta} > \kappa \end{cases}, \quad (4)$$

where $B_{t-\Delta} = B(M_{t-\Delta}, X_{t-\Delta})$. In particular, firms remain locked in their prior technology choice in the inaction region $B_{t-\Delta} \in [0, \kappa]$. Define $a_{c \rightarrow e,t} = \mathbf{1}\{x(c, B_{t-\Delta}) = e\}$ and $a_{e \rightarrow c,t} = \mathbf{1}\{x(e, B_{t-\Delta}) = c\}$. Since the arrival of the option to revise is independent of the current technology choice, the change in the number of firms using technology e , $\Delta X_t \equiv X_t - X_{t-\Delta}$, is given by:

$$\Delta X_t = (1 - e^{-k\Delta}) (1 - X_{t-\Delta}) a_{c \rightarrow e,t} - (1 - e^{-k\Delta}) X_{t-\Delta} a_{e \rightarrow c,t}. \quad (5)$$

The first term captures changes due to firms adopting e , while the second term captures changes due to firms abandoning e in favor of c .

Equilibrium An equilibrium of the model is a technology choice rule, x , mapping $\{c, e\} \times \mathbb{R} \rightarrow \{c, e\}$, and a function for the gross adoption benefit, B , mapping $\mathbb{R} \times \mathbb{R} \rightarrow \mathbb{R}$, such that the technology choice rule and the gross adoption benefit solve the system of equations (3)-(4) when X_t follows the law of motion given by (5), and cash follows the law of motion in (2).

Discussion of key assumptions There are three key assumptions in this model. First, the technology e features positive external returns with respect to adoption by other firms in the industry. We do not provide a precise microfoundation for these external returns, but instead focus on their implications for adoption. Nevertheless, this assumption could capture, for instance, external returns arising in a two-sided market, where a high level of adoption among firms incentivizes customers to adopt the platform, and conversely, a high participation by customers on the platform raises the benefits of adoption for firms. The particular form dependence of profits on X_t assumed in this paper for profits can be thought as a reduced-form way of capturing the external returns that would likely arise in equilibrium in that more complicated model. Alternatively, external returns could arise from spillovers across firms in learning how to use the technology.

The second key assumption is that there are fixed costs in the adoption of the technology. While, for reasons we discussed above, we view pecuniary adoption costs of the specific technology we study in this paper as likely to be low, introducing them in the model allows us to broadly discuss the distinguishing

	Complementarities ($C > 0$ and $\kappa = 0$)	Fixed costs ($C = 0$ and $\kappa > 0$)
P1: Long-run increase in number of users	✓	✓
P2: Long-run increase in likelihood of switching	✓	✗
P3: Adoption depends positively on initial conditions	✓	✗

Table 1: Empirical predictions across versions of the model.

empirical features of complementarities in technology choice relative to fixed costs, which may be more relevant in other settings.

The third key assumption is that firms are unable to continuously adjust their technology choice, but instead must wait, on average, $1/k$ periods before being able to re-optimize their choice (subject to the fixed cost). From a theoretical standpoint, the motivation for this assumption is that some sluggishness in adjustment is necessary in order to break the potential for complementarities to generate multiple equilibria, as emphasized by [Frankel and Pauzner \(2000\)](#). More intuitively, this assumption also captures that firms may have heterogeneous (unobservable) abilities to adjust to market conditions as they change.

3.2 The effects of a cash crunch

We now discuss the effects of a sudden, unanticipated, and large decline in M_t to the technology choices of firms in this model. Throughout, we consider a reduction in M_t of size S at date 0:

$$M_0 = (1 - e^{-\theta\Delta})M^c + e^{-\theta\Delta}M_{-\Delta} - S. \quad (6)$$

Our discussion focuses on the implications of the model for three particular moments: the long-run response of the number of users of e ; the long-run response of the number of firms newly switching to e (“switchers,” in what follows); and the relationship between initial conditions and long-run responses. Table 1 summarizes the predictions of different versions of the model for these moments. The rest of the section discusses these predictions in more detail.

3.2.1 Complementarities ($C > 0$ and $\kappa = 0$)

With externalities ($C > 0$), technology choices depend on firms’ expectations about how the number of users of e will evolve in the future. In principle, this could lead to equilibrium multiplicity, with self-fulfilling expectations. However, with common shocks ($\sigma > 0$) and sufficiently rapid mean-reversion, [Frankel and Pauzner \(2000\)](#) show that there is a unique equilibrium, characterized by a frontier $\Phi(\cdot)$ such that firms adopt e , if and only if $M_{t-\Delta} \leq \Phi(X_{t-\Delta})$. Moreover, [Frankel and Burdzy \(2005\)](#) generalized this result to

the case of mean-reverting shocks.²⁴

A key feature of the equilibrium is the fact that the adoption rule is *increasing* in $X_{t-\Delta}$. By contrast, when $C = 0$, the adoption rule is flat and independent of $X_{t-\Delta}$.²⁵ The slope is positive because adoption benefits depend positively on the current value of the number of users of e , $X_{t-\Delta}$. In turn, this is because, when adoption is sluggish ($k < +\infty$), the number of users of e displays some persistence. Firms re-optimizing their technology choice when $X_{t-\Delta}$ is currently high can expect it to stay high, at least in the near future. This raises the incentive to adopt e , so that the level of $M_{t-\Delta}$ must be higher in order to dissuade firms from moving to e .

The dynamics implied by this adoption rule are illustrated in Figure 5. This panel plots the adoption threshold $\Phi(\cdot)$ as well as two different trajectories, one (in red) for a district which starts from a low number of firms using technology e , and another (in blue) for a district which starts from a higher number of firms using technology e .

When the number of users is initially low (red line), the economy jumps from point A to point B as the negative shock to M_t occurs. Firms then start switching from c to e . But eventually, the economy reaches point C , on the adoption threshold. The economy then moves to the region in which abandoning e is optimal. Eventually, the economy converges back to point A . In this instance, the shock thus only has a temporary effect on technology choices.

On the other hand, if the initial number of firms using technology e , $X_{-\Delta}$ is sufficiently high, it can be the case that X_t does not converge back to initial level, but instead, converges to 1. This is illustrated in the blue trajectory in Figure 5. On that trajectory, once the shock has taken place, the district permanently remains below the adoption threshold. In this case, the number of firms using e increases *permanently*, despite the fact that the shock is transitory. Importantly, firms that obtain the possibility of revising their technology choice always opt for e , even long after the shock has dissipated. As a result, the likelihood of switching also increases permanently. Thus, the model features *positive* state-dependence with respect to initial adoption rates.

We next provide an illustration of the quantitative properties of the model, by simulating the response of a large number of districts to the shock. These districts are assumed to have heterogeneous exposures to the aggregate shock S ; namely, district d 's shock is given by:

$$M_{d,0} = (1 - e^{-\theta\Delta})M^c + e^{-\theta\Delta}M_{d,-\Delta} - e^{\epsilon_d}S, \quad \epsilon_d \sim N(-\sigma_D^2/2, \sigma_D^2).$$

²⁴Specifically, they provide technical restrictions on the stochastic shock process so that unicity is guaranteed. Our constant rate of mean reversion falls under the restrictions formulated in assumption A2 of their paper. The working paper version of [Guimaraes and Machado \(2018\)](#) also discusses this issue. We thank Bernardo Guimaraes for clarifying this point.

²⁵See appendix B for a discussion of the frictionless case ($C = 0$ and $\kappa = 0$).

The average path of cash is reported in Figure D.2. Districts are otherwise identical, save for their initial conditions $(M_{-\Delta,d}, X_d)$, which reflect the ergodic distribution of the model prior to the shock.²⁶

Figure D.3 shows the average response across districts. Consistent with the aggregate data discussed in the previous section, the number of firms using e increases permanently (left panel of Figure D.3). Moreover, the likelihood of switching also increases permanently (right panel of Figure D.3).

This average response masks substantial heterogeneity across districts. First, districts which (all other things equal) experience a larger decline in M (that is, have a higher exposure e^{ϵ_d}) are more likely to remain in the adoption region in the long-run. Indeed, quantitatively, the model predicts that the long-run response of the number of users of e (the left panel of Figure 6) is increasing in the exposure of the district to the shock, e^{ϵ_d} .

Second, districts with different initial conditions will also experience different long-run adoption dynamics (for a given exposure level). As discussed above, we should expect districts with high initial adoption to respond more to the shock, all other things equal. That is, the long-run response should be state-dependent, where the word “state” here refers to the endogenous state variable of the district, the initial number of users of e , $X_{0,d}$. The numerical simulations confirm this. The right panel of Figure 6 shows that the long-run response of both the number of users of e is increasing in the level of initial adoption, $X_{0,d}$. This results highlights the broader idea that long-run adoption dynamics are determined by the initial strength of complementarities.

3.2.2 Fixed costs ($C = 0$ and $\kappa > 0$)

In the model with only fixed costs, firms’ technology choice follows a simple (S, s) rule. Two boundaries, \underline{M} and \overline{M} , fully characterize technology choices: a firm chooses to switch to e if $M_t < \underline{M}$, to switch to c if $M_t > \overline{M}$, and the status quo when $\underline{M} < M_t < \overline{M}$. As illustrated in Figure 7, a large shock moves the economy from its initial state (point A) to the adoption region (point B); but in finite time, the economy reaches the boundary \underline{M} again (at point C). At that, point adoption ceases, but firms that receive the technology adjustment shock choose inaction, so that the fraction of users of e stays constant. Thus, large temporary shocks can have permanent effects on the number of users, just as in the model with complementarities. However, differently from the model with complementarities, the likelihood of switching does not increase permanently: it goes to zero as the shock dissipates.

An additional feature of the model with fixed costs is that it features *negative* state-dependence of adoption with respect to initial conditions, $X_{0,d}$. The expected time to go from point B (the point to which

²⁶Appendix B reports the details of our numerical solution method for the model; it uses iterated deletion of strictly dominated strategies.

the economy is brought after the shock) to point C (the point at which the inaction region is reached again) does not depend on the initial number of users of e . Because the law of motion for X_t , from B to C , is simply $\Delta X_t = (1 - e^{-k\Delta})(1 - X_{t-\Delta})$, the cumulative change in X_t is a decreasing function of the initial number of users, X_0 . This negative state-dependence is a consequence of the assumption that the total number of firms is fixed. Nevertheless, it stands in contrast to the model with complementarities.

Figures D.4 and D.5 further highlight these differences with respect to the complementarities model. Figure D.4 reports the average response of the economy to the shock. The number of users increases permanently, but the likelihood of switching goes to zero after the shock has dissipated. Consistent with the long-run response of the number of users overall, across districts with different exposures to the shock, the long-run response of the number of users is positively related to shock exposure (left panel of Figure D.5). However, as reported on the right panel of Figure D.5, the long-run response of the number of users is negatively related to initial conditions, instead of the positive relationship predicted by the model with complementarities.

3.2.3 Shock persistence

This discussion of the complementarities case ($C > 0$ and $\kappa = 0$) focused on versions of the model where $\theta > k$, that is, the speed at which firms may adjust their technology choice is slow relative to the speed of mean-reversion of the shock. Under the alternative assumption ($\theta < k$), the pure complementarities model tends to generate a *stronger* permanent switch to e after the shock, but a *weaker* (and, in fact, *negative*) relationship between initial conditions and subsequent increases in the number of users, e .

The first part of this claim is illustrated in Figure D.6, which reports the adoption dynamics in a version of the model where $\theta < k$. The average fraction of firms using technology e rapidly converges to 1 after the shock, reflecting the fact that firms frequently receive the technology adjustment shock. As a result, adoption converges to 1, and the likelihood of switching also increases, as illustrated in Figure D.7.

Importantly, this occurs independently of whether the initial adoption rate is high or not. As a result, there is little dependence on initial conditions — all districts tend to converge to $X_\infty = 1$ in this case. The right panel of Figure D.8 illustrates this. There is a weak negative relationship between the change in the number of users and initial conditions when $\theta < k$, instead of the strong positive one when adjustment is more sluggish ($\theta > k$).

This interaction between shock persistence and state-dependence of responses has implications for policy. One might have thought that the presence of complementarities gives policymakers unusually strong powers in triggering technology adoption: temporary interventions can indeed have permanent effects. But in fact, the model indicates that this only occurs when the shock is sufficiently persistent, that is, when θ is below k .

Instead, the more temporary the intervention is (that is, the higher θ is, in particular relative to the speed of adjustment of firms, k), the more likely it is that it will have heterogeneous effects across districts. Moreover, these effects will increase with initial adoption rates. Thus, very temporary interventions will do nothing more than accentuate differences in initial technology adoption. A policymaker with a preference for temporary interventions will therefore face a trade-off between the persistence of the shock and its distributional effects. This implication of the model also reinforces the importance of documenting state-dependence in the data.

There are three main take-aways from the analysis of the model. First, both the fixed cost and the complementarities model can generate persistent adoption following the temporary shock. Second, only the complementarities model can generate long-run increases in the likelihood of switching. Third, the complementarities model is characterized by a positive relationship between long-run adoption and the initial strength of complementarities. The latter two predictions, which are likely to survive in a more general model where *both* fixed costs *and* complementarities are active ($C > 0$ and $\kappa > 0$), can thus help us identify the presence of complementarities in the data. This is the question we turn to in the next section.

4 Adoption Dynamics

So far, Section 2 showed that, in aggregate, the demonetization was followed by a wave of adoption of electronic payment systems. Moreover, the increase in the use of electronic payment systems was persistent, despite the fact that the demonetization’s effects on the supply of cash were relatively short-lived. Section 3 then analyzed a model of technology adoption that can rationalize these observations using either one of two potential mechanisms: fixed costs of adoption, or complementarities across firms in adoption decisions.

The goal of this section is to further test the model’s predictions, particularly those (reported in Table 1) that are specific to complementarities. The two key predictions that characterize complementarities can be summarized as follows: first, the shock causes an increase in the likelihood that firms will switch to the platform, which persists beyond the shock itself; second, the size of the long-run change in adoption caused by the shock is positively related to initial adoption rates and to the initial strength of complementarities more generally, a prediction we refer to as “state-dependence.”

We start by briefly describing the data we use in our analysis. We then develop a novel quasi-experimental framework to estimate the causal impact of the cash-contraction across Indian districts. Using this method, we show that the shock not only caused a persistent increase in overall adoption, but also led to an increase in the overall rate at which new firms switch to the platform, and that this increase persisted substantially beyond the cash crunch. We then use three separate empirical settings to test for state-dependence, and

show that in all three, adoption following the shock was higher in situations where the initial strength of complementarities was stronger.

4.1 Data

The main data source we use in our analysis are merchant-level transactions from one of the leading digital-wallet companies in the country.²⁷ We observe the sales amount and number of transactions on a weekly basis for anonymized merchants between May 2016 and June 2017.²⁸ For each merchant, we also know the location of the shop at the district level, as well as the store’s detailed industry. For a random sub-sample of shops, the location is provided at the more detailed level of 6-digit pincode.²⁹ There are two key advantages of these data relative to other data on electronic payment available for this setting. First, it is relatively high frequency, since we can aggregate the data at weekly or monthly levels. Second, the transactions are geo-localized, therefore allowing us to aggregate them up at the same level as other data sources used in this study.

We obtain data on district-level banking information from the Reserve Bank of India (RBI). This includes three pieces of information: first, the number of bank branches and banks operating these branches; second, information on the number of currency chests by district and the banks operating the chests; third, quarterly bank deposits at the bank-group level in each district.

Finally, we complement these data with information from the Indian Population Census of 2011 to calculate a large set of district-level characteristics. These characteristics include: population, banking quality (share of villages with an ATM and banking facility, number of bank branches and agricultural societies per capita), measures of socioeconomic development (sex ratio, literacy rate, growth rate, employment rate, share of rural capital) and other administrative details including distance to the nearest urban center.

4.2 Heterogeneous shock exposure

4.2.1 Measuring exposure at the district level

In the first part of the paper we have shown that the demonetization was associated with a large increase in the use of electronic payment systems. This section will develop a novel empirical strategy to estimate the causal effect of the cash contraction across districts. This extra step is important for two reasons. First,

²⁷The specifics of the payment technology offered by the company are described in the introduction as well as in Section 2. During the period of our study, the mobile platform was the biggest firm in the market providing mobile transaction service. Since March 2017, few other public platforms have emerged because of the government’s initiative of “cashless economy”.

²⁸The company shared with us information on the top million firms using the platform during this period. This sample represents the almost totality of transactions - in both number and value - conducted using the technology and the largest majority of firms that has signed up for the platform.

²⁹A pincode in India is the approximate equivalent of a five-digit zip-code in the US. Pincodes were created by the postal service in India. India has a total of 19,238 pincodes, out of which 10,458 are covered in our dataset.

the model from Section 3 makes a stronger prediction, showing that the increase of adoption should also be positively related to the size of the shock at the local level, as highlighted in the left panels of Figures 6 and D.5. Second, the event-study framework discussed in 2 is well-suited for examining the immediate reaction to a large shock, but it can have limitations when looking at medium-run responses. Over a longer-horizon the estimates of an event-study may be confounded by other aggregate shocks that may follow the initial policy-intervention.³⁰

To identify heterogeneity in the exposure to the cash contraction at the local level, we construct a measure of shock that exploits heterogeneity across districts in the relative importance of chest banks — defined as banks operating a currency chest in the district — in the local banking market. In the Indian system, currency chests are branches of commercial banks that are entrusted by the RBI with cash-management tasks in the district. Currency chests receive new currency from the central bank and are in charge of distributing it locally. While the majority of Indian districts have at least one chest bank, districts differ in the total number of the chest banks, as well as in chest banks’ share of the local market.

Consistent with anecdotal evidence, we expect that districts where chest banks account for a larger share of the local banking market should experience a smaller cash crunch during the months of November and December.³¹ On some level, this relationship is mechanical. Chest banks were the first institutions to receive new notes, so where chests account for a larger share of the local banking market, a larger share of the population can access the new bills. Furthermore, the importance of chest banks may be an even more salient determinant of access to cash if these institutions were biased toward their own customers or partner banks. Indeed, concerns of bias in chest-bank behavior were widespread in India during the demonetization.³²

To measure the local importance of chest banks, we combine public data on the location of chest banks with information on overall branching in India and data on bank deposits in the fall quarter of the year before demonetization (2015Q4). Ideally, we want to measure the share of deposits in a district held by banks operating currency chests in that district. However, data on deposits are not available at the district level for each bank. Instead, the data are only available at the bank-type level (G_d).³³ Since we have

³⁰In this context, there may be several aggregate factors that may play a role. Among the potential confounding factors, we note a change in the marketing strategy of the electronic-wallet company (e.g. the announcement of a fee in February), changes in the competitive environment of the electronic payment industry starting in March 2017, and a series of discretionary RBI directives to encourage the use of electronic payments during the early months of the demonetization (for a description of the latter, see RBI, 2017). Additional aggregate macroeconomic events potentially confounding the demonetization include the US election, which occurred on the same day as the demonetization, a better-than-usual monsoon, and the launch of the Goods and Services tax, a VAT tax, on July 1, 2017.

³¹In the popular press, several articles argue that proximity — either geographical or institutional — to chest banks contributed to the public’s ability to have early access to new cash. For instance, see <https://www.thehindubusinessline.com/opinion/columns/all-you-wanted-to-know-about-currency-chest/article9370930.ece>.

³²In a report in December, the RBI has discussed this issue extensively. In one comment, they report how “these banks with currency chests are, therefore, advised to make visible efforts to dispel the perception of unequal allocation among other banks and their own branches.” See <https://economictimes.indiatimes.com/news/economy/finance/banks-with-currency-chest-need-to-boost-supply-for-crop-rbi/articleshow/55750835.cms?from=mdr>.

³³The RBI classifies banks in six bank groups: State Bank of India (SBI) and its associates (26%), nationalized banks (25%),

information on the number of branches for each bank at the district level, we can proxy for the share of bank deposits of each bank by scaling the total deposits of the bank type in the district by the banks' share of total branches in that bank type and district.³⁴ We can then compute our score as:

$$\text{Chest}_d = \frac{\sum_{b \in C_d} \sum_j D_{jbd}}{\sum_{b \in B_d} \sum_j D_{jbd}} \approx \frac{1}{D_d} \left(\sum_{g \in G_d} \left(D_{gd} \times \frac{N_{gd}^c}{N_{gd}} \right) \right)$$

where D_d is the total amount of deposit in the district d , D_{gd} and N_{gd} are respectively the amount of deposits and the number of branches in bank-type g and district d , and N_{gd}^c is the number of branches in the district for a bank with at least one currency chest in the area.³⁵ Since we want to interpret our instrument as a measure of the strength of the shock, our final score Exposure_d is simply the inverse of the above chest measure *i.e.* $\text{Exposure}_d = 1 - \text{Chest}_d$. Figure D.9 plots the distribution of this exposure score across districts. The figure shows a very smooth distribution centered on a median around 0.55, with large variation at both tails (a standard deviation of 0.18). Overall, chest exposure appears to be well-distributed across the country, as very high and very low exposure districts can be found essentially across every region in the country (Figure 8). Consistent with this idea, in the robustness section we will show how results do not depend on any specific part of the country.

Intuitively, areas where chest banks are less prominent — or high exposure according to the index — should have experienced a higher cash contraction during the months of November and December. Given that the data are not publicly available, this hypothesis cannot be tested directly. However, as discussed in Section 2, the cash crunch occurred because old notes had to be deposited by the end of the year, but withdrawals were severely limited. Therefore, the growth in deposits during the last quarter of 2016 proxies for the cash contraction in the local area. Figure D.10 provides evidence that is consistent with this intuition. Here, we plot the distribution of deposit growth across Indian districts in the last quarter of 2016 versus 2015. In normal times (2015), we see that the distribution is relatively tight around a small positive growth. During the demonetization, the distribution looks very different. First, almost no district experienced a contraction in deposits. Second, the median increase in deposits was one order of magnitude larger than during normal times. Third, the data overall show much more dispersion across districts, suggesting that the effect of the demonetization was likely not uniform across Indian districts.³⁶

regional rural banks (25%), private sector banks (23%) and foreign banks (1%).

³⁴A simple example may help. Assume we are trying to figure out the local share of deposit by banks A and B, both rural banks. We know that rural banks in aggregate represents 20% of deposits in the district, and we know that bank A has 3 branches in the district, while bank B only has one. Our method will impute bank A's share of deposits to be 15%, while bank B's will be 5%.

³⁵In practice, this approximation relies on the assumption that the amount of deposits held by each bank is proportional to the number of branches within each district. The strength of our first-stage analysis suggests that this approximation appears to be reasonable.

³⁶The result is essentially the same if we compare 2016 with data from 2014 on deposit growth dispersion.

Building on this intuition, we then show that our exposure measure indeed proxies for the severity of the cash crunch at the local level. Figure 9 shows that there is a strong relationship between district-level exposure to the shock and deposit growth. The same relationship holds when using different measures of deposit growth and including district-level controls, as shown in Table D.1. More importantly, Table D.2 also shows that this strong relationship is unique to the demonetization quarter.³⁷

4.2.2 Results

Using this measure of exposure, we estimate the following difference-in-difference model:

$$\log(y_{d,t}) = \alpha_t + \alpha_d + \delta (\text{Exposure}_d \times \mathbf{1}_{\{t \geq t_0\}}) + \Gamma'_t Y_d + \epsilon_{d,t}, \quad (7)$$

where t is time (month), d indexes the district, t_0 is the time of the shock (November 2016), and Exposure_d is the measure of district's exposure constructed with chest-bank data, as explained above. The equation is estimated with standard errors clustered at the district level, which is the level of the treatment (Bertrand et al., 2004). Lastly, the specification is based on the data between May 2016 and June 2017.³⁸

Importantly, the specification is also augmented with a set of district-level controls (Y_d), which are measured before the shock and interacted with time dummies. The presence of controls is important for the causal interpretation of our results, because chest exposure is clearly not random. Table 2 examines this issue, by showing the difference across characteristics for districts characterized by different exposure. In general, exposure to chest banks is actually uncorrelated with several district-level demographic and economic characteristics, but not all of them. In particular, higher exposure (lower density of chest banks) is found in districts with a smaller deposit base, smaller population, and larger share of rural population. However, most of the variation in exposure is absorbed once we control for two simple determinants of the local banking market: the size of the deposit base in the quarter before the shock and the percentage of village with ATM (last columns, Table 2). Taking a more conservative approach, our controls will include the log of deposits in the quarter before the demonetization, the percentage of villages with an ATM, the log of population, the share of villages with a banking facility, and the share of rural population.

Using this model, we now examine the causal effect of the cash contraction on technology adoption, mapping our results to the predictions of the model. After presenting the results, we will also discuss further

³⁷In particular, the Table uses data since 2014 and shows that – in normal time – the relationship between these two quantities is small and generally insignificant. In the only case in which this relationship is positive, we find that the relationship is several order of magnitude smaller than in 2016Q4.

³⁸We exclude sparsely populated northeastern states and union territories from the analysis due to missing information on either district-level characteristics or banking variables. The seven north-eastern states include Arunachal Pradesh, Manipur, Meghalaya, Mizoram, Nagaland, Sikkim, and Tripura while union territories include Anadaman and Nicobar Islands, Chandigarh, Dadra and Nagar Haveli, Daman and Diu, Lakshadweep and Pondicherry. Altogether these regions account for 1.5% of the total population of the country.

evidence on the causal interpretation of our analyses.

Exposure and adoption In Table 3, we start by showing that the exposure to the cash-contraction predicts the response across districts. In the first two columns, we examine the effect on the amount of transactions undertaken using the wallet technology. We find that districts that were more exposed to the shock saw a larger increase in the amount of usage of electronic payments in the months following the demonetization. This result is both economically and statistically significant. Comparing two districts one standard deviation apart in terms of exposure, we find that the more exposed one experienced an increase of 55 % in the amount transacted on the platform relative to the average (Column 1). Similarly, the number of firms operating on the platform — our main measure of adoption — increased by 20% in districts with one standard deviation higher exposure to the shock.

In Figure 10 (first two panels) we plot the dynamic of the main effect, which is we estimate how districts characterized by different level of exposure responded to the shock month-by-month.³⁹ This figure highlights three main findings. First, we confirm that our main effect is not simply driven by differential trends between high- vs. low-affected areas. Second, we find that the shift in adoption across districts happened as early as November. However, the effect is in general larger in December and January. Third, we find that the difference in the response also persists after the cash availability returns to normal level. In particular, the effects are still large and significant after the month of February. We find consistent results across both the amount of transactions and the number of firms using the technology. In line with the initial aggregate evidence, this analysis confirms that the temporary cash contraction led to a permanent increase in the adoption of payment technologies.

Next, we examine how the shock affected the initial decision of firms to use the technology.⁴⁰ As we have shown with the model in Section 3, for a technology characterized by externalities a sufficiently large shock will not only raise the total number of users, but it will also have a persistent effect on the rate of adoption of the new technology. Without externalities, the shock may have some persistent effect (fixed-cost model), but the increase will be concentrated at the height of the shock and no extra firm will join the platform outside the period in which cash is scarce.

To examine this question, we now test whether districts that were highly affected by the shock saw a persistent increase in new adopters (e.g. firms using the technology for the first time). Results can be

³⁹To be precise, we estimate the following equation (October is the normalized month):

$$\log(y_{d,t}) = \alpha_t + \alpha_d + \delta_t (\text{Exposure}_d \times \mathbf{1}_{\{t \geq t_0\}}) + \Gamma'_t Y_d + \epsilon_{d,t}. \quad (8)$$

⁴⁰To be conservative, we measure the number of active firms in the platform as firms with at least 50 Rs. of transaction in the period. Results using different transaction threshold and in particular a threshold of zero are similar (available in the previous versions of the paper).

visualized directly in the third panel of Figure 10.⁴¹ As expected, we find that districts experiencing a larger contraction in cash saw a larger increase in new firms joining the platform as early as on November 2016. But firms in highly affected areas kept joining the platform at a higher rate after January 2017, the last month during which cash withdrawal was constrained. The relative increase in highly exposed districts appears to persist for the whole spring 2017.

Thus, districts experiencing higher cash contractions saw a larger and persistent increase in the usage of electronic payments. Additionally, consistent with a model characterized by externalities, this effect is partly explained by the fact that the shock led to a persistent increase in the number of firms joining the platform. We argue that this relationship between cash contraction and adoption of new electronic payment is causal. To argue in favor of this interpretation, we have shown that - conditional on covariates - highly affected areas do not look different than low affected regions. At the same time, our effects are not driven by lack of pre-trend across affected districts.

One remaining concern to rule out is the presence of a contemporaneous demand shock that is correlated with our exposure measure but it is unrelated to the cash scarcity. To assuage this concern, it is important to highlight two tests that will be presented later in the paper (Section 6). First, we will show that the same highly affected districts also experienced a larger decline in consumption during this period. This joint effect on electronic payment and consumption can be easily explained by the cash contraction, but it would be inconsistent with any demand side explanation.⁴² Second, to further bolster the identification, Section 6 will also present a full set of placebos that exploit the longer-panel dimension in the consumption data and confirm the quality of our empirical strategy.

Lastly, it is important to highlight how our main results are not driven by any specific part of the country. While the exposure measure based on chest bank is fairly well distributed across India, you may still be concerned that the effects are driven by the behavior of a sub-set of the whole country. To exclude this possibility, in Figure D.11 we repeat the main specification by dropping one at the time all states in India. In particular, the Figure reports the coefficient from the regression where the outcome is the amount of transactions in the district with the 95% confidence interval. In the x-axis we report the name of the state that was dropped, while the horizontal dashed line reports the coefficient from the analysis using the full sample. In every analysis, we find that coefficient remains positive and significant with the reduced sample. More importantly, the magnitude of the coefficient is also very stable and it never significantly depart from

⁴¹We define a firm as new if it uses the platform for the first time in our data.

⁴²One demand story may be the following. The demonetization clearly also increased overall policy uncertainty in the country, and this increase in uncertainty may hurt different regions differently because of some heterogeneity in the local industry mix. If our exposure measure is negatively correlated with the local effect of uncertainty, we may find a relative increase in electronic payment simply because economic activity in our exposed region contracted less than the less exposed region. While this correlation structure could explain the effect on electronic payment adoption, it would then be inconsistent with the consumption effect.

the our estimate using the full sample.

4.3 State-dependence in adoption dynamics

One of the key predictions of the model with complementarities is the state-dependence of adoption. In particular, the model suggests that a temporary shock may lead to a permanent shift in adoption, but that the increase in adoption will not be uniform across areas: it will crucially depend on the initial strength of complementarities in the area. For instance, in the simulations we have shown that there is a strong positive relationship between the initial number of users and the increase in adoption (see the right panel of Figure 6).

In this Section, we use the data on electronic payments to present three pieces of evidence that are consistent with this model’s prediction. Conceptually, the objective of these tests is not to causally identify a relationship between variables, but rather to generate empirical regularities that would support the importance of state-dependence in explaining the data. To do so, we are going to try to isolate the role of the state-dependence mechanism from alternative economic forces that could explain the same results. While none of the tests will be perfect in nature, we believe that all of them together provide convincing evidence on the empirical relevance of the model.

4.3.1 District-level evidence

In the theory section, we modeled state-dependence by showing how the strength of the complementarities before the shock predicts the path of a district in response to the shock (see the right panel of Figure 6). In this subsection, we provide evidence that is closely related to that result.

In particular, the model directly predicts that the initial level of adoption in a district should amplify the adoption response to the shock. The intuition is the usual: a larger number of initial adopters increases the benefit of switching to the technology and will therefore increase the likelihood of moving into a higher adoption equilibrium. In Table D.4, we provide evidence that the data are consistent with this prediction.⁴³ Across two specifications, we find that a high initial level of adoption at the district level tends to be correlated with a higher change in adoption after the shock.

This *within-district* evidence is thus consistent with state-dependence as defined in the model. However, several shortcomings characterize this approach. First, inference based on this model is likely to suffer from the standard reflection problem (Manski, 1993; Rysman, 2019). In this case, the reflection problem would

⁴³Specifically, we estimate:

$$X_{d,t} = \alpha_t + \alpha_d + \delta (I_d \times \mathbf{1}_{\{t \geq t_0\}}) + \Gamma'_t Y_d + \epsilon_{d,t}, \quad (9)$$

where I_d is a measure of initial adoption levels in a district measured using a either dummy if a district had a positive adoption level before the demonetization or the total amount of transactions in the district before the demonetization.

arise because districts characterized by different levels of initial adoption could present different dynamics of adoption around the shock, even in absence of externalities. Second, the scope of complementarities may extend beyond the district. For example, if complementarities are due to a shared customer base, then it is unclear whether adoption at the district level is the correct way to proxy for their initial strength.

To address these concerns and provide further evidence on state-dependence at the district level, we develop an alternative test that exploits variation across districts. In particular, we test how the increase in adoption differs depending on the distance between a district and areas in which the usage of electronic wallets was large *prior* to November (*hubs*). The mapping between the strength of complementarities and distance to the electronic payment hub is intuitive. In the model, the heterogeneity in the strength of complementarities is completely determined by the number of users in the same area. In reality, individuals move across districts and therefore the size of adoption in neighboring districts will also be important. Therefore, being located close to a large hub — a center where electronic payment use is relatively common — may significantly increase the benefits of adoption.

Specifically, we run a simple difference-in-difference model where we compare the usage of wallet technologies around the demonetization period across districts that are differentially close to a digital wallet hub.⁴⁴ The main coefficient of interest is the one on the interaction between a post-dummy and the measure of distance at the district level.⁴⁵

Despite the clear advantages relative to the naive *within-district* model, there are two main concerns with this model. First, by sorting on distance we may get identification from areas that are located in more extreme or remote parts of the country. Second, since the electronic hubs are some of the largest and more important cities in the country, we should expect that being located close to them will have benefits that go beyond the effect of complementarities. In other words, distance may capture other forms of heterogeneity that may affect the response to the shock independently from complementarities.

We deal with these limitations in three ways. First, we limit the comparison to districts that are located within the same state, adding state-by-month fixed-effects. In this way, we only exploit distance variation between areas that are already located in similar parts of the country. The results also hold with this set of fixed effects. Second, we also control for the distance to the capital of the state, also interacted with time effects. This control allows us to isolate the effect of the distance to a major electronic payment hub from the effect of being located close to a large city. Third, we augment the specification with a wide set of

⁴⁴In particular, we define a district to be an electronic payment hub if there were more than 500 of active firms pre-demonetization (September 2016). The results are essentially identical if we use a threshold of 1,000 firms to define the hub districts. The distance to the hub is defined as the minimum of the distance between the district and all the hubs.

⁴⁵There are nine electronic payment hubs with more than 500 active firms pre-demonetization and are spread evenly across the country: Delhi, Chandigarh and Jaipur (North), Kolkata (East); Mumbai and Pune (West); Chennai, Bangalore and Rangareddy (South). These nine districts are also among the top metropolitan cities by population in India.

district-level covariates interacted with the time dummies.⁴⁶

The general specification is therefore a difference-in-difference model of the following form:

$$X_{d,s,t} = \alpha_{st} + \alpha_d + \delta (D_d \times \mathbf{1}_{\{t \geq t_0\}}) + \gamma (\tilde{D}_{d,s} \times \mathbf{1}_{\{t \geq t_0\}}) + \Gamma'_t Y_d + \epsilon_{d,t}, \quad (10)$$

where t indicates time, defined at the monthly level in this analysis, d indexes the district and s identifies the state of the district. D_d is the district's distance to the nearest electronic-wallet hub and $\tilde{D}_{d,s}$ is the district's distance to the capital district of the state. The equation is estimated with standard errors clustered at district level, which is the level of the treatment. It is important to point out that we exclude from this analysis the districts defined as major digit wallet hubs.⁴⁷ The main coefficient of interest is δ — which provides the difference in the level of adoption pre- and post-demonetization depending on how far the district is from its closest electronic-wallet hubs.

These results are reported in Table 5. In odd columns, we report the baseline regression where we control for the distance to the state capital as well as the other controls at the district-level, interacted with month-dummies. Across all the outcomes — the amount of transactions, number of operating firms and number of new adopters — we find that the districts farther away from major hubs experienced a lower increase in the post-demonetization period. The same result holds when adding the state-by-month fixed-effects (even columns). If we take the most conservative of the estimates, we find that a 50 *km* increase in distance translates into a 19% lower increase in the amount of transactions. Lastly, we find similar results when we use a dichotomous definition of the treatment (Table D.5).⁴⁸

Lastly, Figure 12 allows us to explore the dynamics of the effect. We construct this figure by replicating the same analysis as before but estimating a month-specific effect for every month around the demonetization, normalizing the month of October to zero. The dynamic effects confirm that our results do not simply pick up a secular trend in adoption between major hub cities and their neighboring areas. In fact, we find essentially no relative difference in adoption before October. Furthermore, this figure also reveals that some of the initial kick in adoption is caused by being located close to a large hub and it does not disappear as cash withdrawal constraints are relaxed.

Overall, these results help shed light on the mechanism behind the technology adoption wave in the aftermath of the demonetization. We show that adoption was stronger in areas that had initially high adoption rates; moreover, the increase was stronger in areas that were geographically relatively close to the major electronic-wallet hubs before the shock. Both of these results are consistent with strong state-

⁴⁶Our controls are the same as those used in the previous chest bank regression.

⁴⁷Notice that this exclusion does not affect our results; the results that includes the hubs are, if anything, stronger.

⁴⁸In particular, we consider several alternatives, going from 400*km* down to 200*km*. Across all these tests, the results are stable and significant.

dependence in adoption.

4.3.2 Firm-level evidence

Next, we examine the role of state-dependence using firm-level data. This approach has two key advantages relative to the district-level regressions. First, firm-level data will allow us to control for several dimensions of firm-heterogeneity that may explain adoption decisions for reasons unrelated to externalities. Second, using firm-level data will allow us to map more directly the data to the model. In particular, in the model, we can write the use of the technology by firm i at time t in area d as a function of its use of the technology in the previous period, the level of the aggregate shock, and the level of adoption by other firms in the same market.⁴⁹ Under the assumption that the technology is characterized by positive externalities ($C > 0$), the level of adoption by other firms in the same area will positively predict the adoption by the firm (Column 2 of Table D.3). The intuition for this result is simple: an increase in the use of the technology will increase the value of the technology itself, which will in turn positively affect adoption by firms. Importantly, the same relationship will not hold without externalities (Column 1 of Table D.3).

Therefore, the model implies a positive relationship between a firm’s use of the technology and the overall use by other firms in the same area. This idea is consistent with the approach used in other settings to test for the presence of spillovers in behavior (e.g. Munshi (2004), Goolsbee and Klenow (2002)).⁵⁰ In our context, this relationship will create state-dependence, because differences in the initial level of adoption across markets will endogenously affect the pattern of adoption in the future.

We leverage on the granularity of the data to test for the presence of this relationship in our setting. For each firm, we measure the total use of the technology by firms that are located in the same geographical area and that operate in the same industry. We choose this set of firms as a reference group because we believe that complementarities should be strongest among firms in the same area and industry. In particular, we expect to find the largest overlap in customers for companies within the same area and industry, as well as the largest spillovers in learning about the value of the technology. However, later we will also consider alternative definitions of the reference group in robustness checks.

Next, we test whether technology use, for one firm, is indeed positively related to the use of the technology

⁴⁹To be precise, we could estimate a firm-level regression in the simulated data of the following form:

$$x_{i,d,t} = \alpha + \rho x_{i,d,t-\Delta} + \beta M_{d,t-\Delta} + \gamma X_{d,t-\Delta} + \epsilon_{d,t} \quad (11)$$

⁵⁰For instance, Munshi (2004) uses a similar methodology to explore the role of social learning in agriculture in rural India, while Goolsbee and Klenow (2002) examines the adoption of home computers in US.

by other firms in its reference group in prior periods. In particular, we estimate:

$$x_{i,p,k,t} = \alpha_i + \alpha_{p,t} + \alpha_{k,t} + \rho x_{i,p,k,t-1} + \gamma X_{p,k,t-1} + \epsilon_{i,p,k,t}. \quad (12)$$

Here $x_{i,p,k,t}$ is a measure of technology choice by firm i in industry k and pincode p at time t (where t is a week). For instance, this measure could be a dummy for whether the firm used the platform, or it could be the amount of activity of the firm on the platform.⁵¹ The variable $X_{p,k,t-1}$ is a measure of adoption by other firms in the same pincode and the same industry during the previous week. To be consistent, we measure $X_{p,k,t-1}$ using the same variable we used as the outcome, summing that dimension across all firms in the same pincode and industry, and always excluding the firm itself. To ease the interpretation of the coefficients, apart from when the outcome is a dummy, we log-transform all the relevant variables.⁵² The model is estimated using weekly data from our electronic wallet company.⁵³ We conservatively estimate our standard errors clustering them by pincode, which allows firm errors to be correlated both across time and across space within the same location.

We start by estimating this equation without any fixed-effects in the first column of Table 4. We find that a higher volume of electronic transactions by firms in the same reference group strongly predicts more transactions for the firm itself in the following week. This effect is not only statistically significant but also quantitatively large. In particular, a one-standard-deviation increase in transactions by firms in the reference group leads to a 40% increase in the amount of transactions for the firm, which corresponds to 18% of the standard-deviation of the outcome variable. The same results hold — with similar magnitude — when we look at the number of transactions or at whether the firm was active on the platform.

Similar to the reflection problem discussed before, the main concern in this analysis is that past decisions by firms in the reference group may correlate with an individual firm’s behavior because this measure would capture some unobservable heterogeneity across firms unrelated to the strength of complementarities. For instance, a certain area may have on average more educated workers, who may then be more likely to adopt the platform, irrespective of complementarities. In this case, past adoption by other firms may simply proxy for the effect of education. In other words, the results could be driven by an omitted variable that is correlated with adoption by other firms but orthogonal to the strength of complementarities.

⁵¹We classify firms into 14 broad industries: Food and Groceries (14%), Clothing (10%), Cosmetics (2%), Appliances (8%), Restaurants (12%), Recreation (2%), Bills and Rent (1%), Transportation (13%), Communication (12%), Education (3%), Health (7%), Services (4%), Jewellery (1%) and Others (11%).

⁵²In other words, we transform each variable to be equal to the log-plus one of the primitive.

⁵³The sample is a balanced panel of all the firms that used the wallet between May 2016 and June 2017 and that have information on location (pincode). We use pincode to identify firms’ locations because we want to use the narrowest definition of location that is available in the data. Unfortunately, the actual pincode is only available for a subset of firms. Later in the section, we also present a robustness using the district to define location — a measure that is broader geographically but available for every firm — and we show that the results do not change.

To assuage this concern, we proceed in three steps. First, we augment the specification with a firm-fixed effect. Since we are now exploiting only within-firm variation, the type of omitted variable that could explain our result would also need to be time-varying. Second, in the third column of Table 4, we add pincode-by-week fixed-effects. This fixed-effect will allow us to keep constant in the model any characteristic of the area, even to the extent that these characteristics have a differential effect over time. Third, we also add a detailed set of industry-by-week fixed-effects (column four of Table 4). Relative to the previous framework, in this specification we not only compare firms within the same location, but we also adjust the estimates for changes in adoption rates in the same industry. Across all these specifications, we consistently find that the adoption intensity by firms in the same reference group is a strongly positive predictor of a firm’s use of the platform.⁵⁴

Until now, our analyses have used the whole panel for firms, using data from both before, during, and after the demonetization. However, one may expect the importance of complementarities to be different in the three periods. The predictions of the model are actually consistent with this intuition. In fact, using the simulated data from the model, we can show that the importance of the adoption by other firms is particularly salient in the shock period.

To explore this hypothesis, we repeat the same analyses as before, but rather than estimating one single parameter for the effect of externality, we estimate a month-specific parameter for each of our outcomes. The results are plotted in the three panels of Figure 11. Across the three outcomes, we draw two main conclusions. First, the positive effect documented before is always present in the data, both before and after the policy shock. This is reassuring, since the state-dependence induced by complementarities is not generated by the shock but should be a feature of technology choices in any scenario. Second, we find that the effects of adoption in the reference group are much higher in the months of the demonetization, relative to the preceding and succeeding months. As previously discussed, this result is also consistent with the model.

Two robustness tests are worth highlighting. First, the results also hold if we define the area of the reference group as the district (Table D.6 in Appendix).⁵⁵ Second, the results are robust when we define the relevant market in a different way. For instance, in Table D.7 in the Appendix we define the relevant market as any firm in the same location (pincode), irrespective of the industry.

⁵⁴The inclusion of fixed-effects in a dynamic model may bias the main parameters in the model, as first discussed in Nickell (1981). However, there are two important things to highlight about our application. First, the presence of fixed-effect is not necessary to obtain the desired result, since we still find the same effect without any fixed-effects (column 1). Second, the Nickell bias is a feature of models characterized by short panels, as the bias converges to zero as $T - 1$ increases, where T is the time-dimension in the panel. In our case, T is relatively large - data is at weekly level and the time span is almost a year - and therefore the bias will be small in magnitude. In particular, since our main prediction is on the direction of the relationship rather than on the exact magnitude, this issue will not affect the conclusion of this study.

⁵⁵One key advantage of this approach is that we have the location based on the district for the whole data. Clearly, with this alternative approach we cannot control for location-by-time fixed effects.

Overall, these results highlight the importance of state-dependence in adoption at the firm-level. Consistent with the model’s implications, we have shown that the use of technologies by neighboring firms positively correlates with adoption at the firm level, and that this effect is particularly strong during the shock period.

4.4 Discussion

There are two key takeaways from this empirical analysis: first, shock exposure predicts both the short- and long-run strength of adoption; second, there is pervasive evidence that adoption was state-dependent, in the sense that stronger initial benefits to adoption – proxied by either adoption in a firms’ area and industry, by initial adoption in the district, or by distance to hubs – predict a higher long-run adoption response.

It is worth mentioning that these results do not rule out the presence of fixed adoption costs. As highlighted by the analysis of the model, fixed adoption costs can in fact generate the set of first findings regarding heterogeneous shock exposure, though it can generate neither the persistent increase in new adoption, nor the state-dependence. Thus, the empirical results require a positive amount of complementarity in adoption in order to be rationalized. However, we should also point out that the costs of adoption in this specific context are likely to be very low.⁵⁶ As a result, a mechanism relying in large part on fixed-cost is not very likely to explain these results.⁵⁷

Additionally, documenting state-dependence is useful beyond the fact that it provides evidence in favor of adoption complementarities. Our evidence suggests that state-dependence explains a substantial portion of the heterogeneity in adoption responses to the shock. From the standpoint of a policymaker, state-dependence should thus be an important concern when considering the potential effects of a temporary intervention targeting technology adoption. More specifically, the state-dependence of (long-run adoption) responses arises when the model has complementarities *and* relatively short-lived shocks, at least compared to the typical adjustment speed of firms. In that case, a key prediction of the model is that the shock could even *widen* the differences in adoption in the long-run, as districts with large initial adoption rates will tend to convert to full adoption, while districts with low initial adoption rates will not shift substantially. The evidence in this section suggests that this is not a second-order concern, but very much a feature of adoption responses in the aftermath of the demonetization. If the inequality of technology adoption is a concern for policymakers, then a more long-term intervention may - as suggested by the model - represent a better solution.

⁵⁶For instance, in our specific example, the electronic wallet does not require any monetary cost, and the set up only requires a phone and a bank account and can be completed in a few minutes.

⁵⁷To be precise, the fixed-cost model would explain a large and persistent increase in adoption only if the net benefit of using the technology is positive (so that firms keep using it after the shock) but also too small to justify adopting it in the pre-period. The small adoption costs thus put a sharp restriction on the size of the net benefits to using the platform.

5 Quantifying the role of externalities in the adoption decision

In this section, we use the theoretical model of section 3 using the district-level adoption data, and use the estimated model to quantify the role of externalities in the adoption wave that followed the demonetization.

5.1 Estimation

We estimate the model using the simulated method of moments. We start by describing briefly our approach, focusing on the intuition for how specific moments help identify different model parameters. We then report the results and discuss model fit.

5.1.1 Methodology and identification

We calibrate two parameters of the model. First, we set $r = -\log(0.90)/12$, corresponding to a time discount rate of 0.90 per year.⁵⁸ Second, we set $\theta = -\log(1 - 0.90)/(82/30)$, where θ is the (inverse of) the persistence of innovations to the money stock. This choice ensures it takes on average 82 days for the aggregate shock to be 90% dissipated. The choice of 82 days corresponds to the time which elapsed between the announcement of the cash swap (November 8th, 2016) and the date at which the government lifted most remaining restrictions on cash withdrawals (January 30th, 2017). Additionally, and without loss of generality, we normalize the long-run mean of $M_{d,t}$ to $M^c = 1$.

We estimate the remaining $N_p = 5$ parameters of the model, $\Theta = (S, \rho, k, \sigma, \tau)$. They are, respectively, the size of the demonetization shock (S), the strength of complementarities in adoption (C), the Poisson arrival rate of the technology switching shock (k), the standard deviation of normal innovations to the money stock (σ), and the profits associated with the electronic payments technology when there is no adoption (M^e). In order to estimate those parameters, we use the following set of regressions, on a balanced panel of districts:

$$\begin{aligned}\Delta_{t_0} X_{d,t} &= \beta + \gamma \mathbf{1}\{t \geq t_0 + 3\} + \delta X_{d,t_0} + \zeta (\mathbf{1}\{t \geq t_0 + 3\} \times X_{d,t_0}) + \epsilon_{d,t}, \\ \hat{v}ar_t(\Delta_{t_0} X_{d,t}) &= \eta + \kappa \mathbf{1}\{t \geq t_0 + 3\} + \mu_t, \\ \hat{v}ar_d(\Delta_{t_0} X_{d,t}) &= \nu + \omega_d,\end{aligned}\tag{13}$$

and we additionally estimate the average of the squared residuals $\hat{\epsilon}_{d,t}^2$ from the first regression in (13), through:

$$\hat{\epsilon}_{d,t}^2 = \xi + \omega_{d,t}.\tag{14}$$

⁵⁸As described in appendix, the model is solved using a discrete time approximation where $\Delta t = 1/10$, so that a time period is approximately one tenth of one month.

In these regressions, d indexes the 512 districts included in our analysis, and t indexes months. The month t_0 is October, 2016 (the last month observed prior to the demonetization shock), and $\Delta_{t_0}X_{d,t}$ is the cumulative change in adoption rates: $\Delta_{t_0}X_{d,t} = X_{d,t} - X_{d,t_0}$. We use the 8 months running from November, 2016 to June, 2017.⁵⁹ We compute the participation rate in each district, $X_{d,t}$, as the ratio of the number of monthly users active on the platform during month t , divided by the number of retailers with less than three employees, which we obtain from the 2014 Census.⁶⁰ Finally, $\hat{v}ar_t(\cdot)$ denotes cross-sectional variances, while $\hat{v}ar_d(\cdot)$ denotes within-district variances.

In order to estimate our 5 data parameters, we use $N_m = 8$ data moments from the regressions above: $\hat{\Xi} = (\hat{\beta}, \hat{\gamma}, \hat{\delta}, \hat{\zeta}, \hat{\xi}, \hat{\eta}, \hat{\kappa}, \hat{\nu})$. Appendix C reports the details of the estimation procedure; in particular, we use the bootstrap, clustering by district, in order to construct the variance-covariance matrix of data moments. Here, we focus instead on the intuition for why the chosen data moments help identify the five estimated parameters.

First, the size of the shock, S , is primarily identified by the short-run adoption caused by the shock, which is $\hat{\beta}$. Absent an aggregate shock, $\hat{\beta}$ is not statistically different from 0, and the magnitude of the coefficient increases with the size of the shock, independent of the existence of complementarities.

Second, the strength of complementarities, C , is primarily identified by the difference between the short and medium-run response of adoption to the shock, $\hat{\gamma}$. (Here, we define “medium-run” as three months after the shock; by then, in the data, cash circulation had returned to pre-shock levels; and, in the model, the aggregate shock is more than 90% dissipated.) Without adoption complementarities ($C = 0$), the short-run adoption wave triggered by the shock has no bearing on the adoption decision of firms further down the road. As a result, once the shock is dissipated, there should be no further adoption by new firms. The model would then predict that $\hat{\gamma} = 0$. By contrast, when adoption complementarities are present ($C > 0$), the short-run adoption wave raises the value of future adoption for other firms, and so new firms continuing adopting even once the shock is dissipated, leading to positive values of $\hat{\gamma}$. Additionally, as discussed earlier in the paper, the dependence of the response to the shock on initial conditions ($\hat{\delta}, \hat{\zeta}$) also helps pin down the strength of adoption complementarities.

Third, the rate at which firms re-set their technology choice, k , is identified using estimates of the between-

⁵⁹We subtract the initial adoption rate in order to eliminate district-specific fixed effects, but results either in levels, or adding explicit fixed effects in the estimation of (13), are similar.

⁶⁰Additionally, we re-normalize the Census retail counts so that at least $n \geq 0$ districts reach full adoption. Specifically, for all districts d , we define $X_{d,t} = \min(N_{d,t}/\bar{N}_d^{(n)}, 1)$, where $N_{d,t}$ is the number of adopters per district, and $\bar{N}_d^{(n)} = \frac{N_{d_n,t_0}}{N_{d_n}} N_d$, N_d is the Census count of retailers in district d in 2014, and d_n is a reference district. The reference district is defined as the district with the n th highest un-normalized maximum adoption rate, i.e. the n th highest value of $\max_t \frac{N_{d,t}}{N_d}$. We do this because it is unclear whether the Census counts properly measure the pool of potential adopters. We experimented with values ranging from $n = 0$ (no normalization) to $n = 10$ (the 10 highest-adoption districts reach full adoption). In all cases, we can reject the null of no complementarities, and estimates of the contribution of complementarities to the long-run change in adoption are largely unchanged, ranging from 40% to 65%. We use $n = 5$ in the estimation that follows.

district variance of the change in adoption, $\hat{\eta}$ and $\hat{\kappa}$. The medium-run variance, $\hat{\kappa}$, is particularly informative about k . With complementarities, if firms reset their technology quickly relative to the persistence of the shock (i.e. k is sufficiently high relative to θ), then all districts will rapidly converge to full adoption, thus leading to lower cross-sectional variance in adoption rates in the medium-run. On the other hand, if firms reset their technology relatively slowly (i.e. if k is sufficiently low relative to θ), the cross-sectional variance in adoption rates will rise in the medium-run, as only certain districts (those with higher initial adoption rates) respond to the shock.

Fourth, the standard deviation of idiosyncratic innovations to districts, σ , is identified using the variance of residuals from the first equation in (13). The residual variation in adoption, after controlling for initial condition, should be driven by district-level shocks. Finally, the rate of profits associated with the electronic payments technology when there is no adoption, M^e , is identified using the variance of within-district adoption rates. In particular, even when there are no complementarities, a lower level of M^e is associated with shorter adoption spells, and therefore lower overall volatility of adoption rates.

5.1.2 Results and model fit

Table 7 reports estimates of the five structural parameters. The point estimate for the size of the shock, S , is 24.6% (with a normal 90% coverage interval of [15.0%, 34.1%]). The parameter S expresses the decline in profits associated with cash-based transactions, relative to their long-run mean. There are two numbers with which this estimate could be compared. On the one hand, recall the cash denominations which were voided by the shock represented 86.4% of the total currency in circulation. The shock size we estimate is much smaller than this, but not all of the voided currency was actively used in transactions prior to shock (though it is difficult to measure exactly what fraction was.) On the other hand, Chodorow-Reich et al. (2018) estimate that the general equilibrium response of output to the shock was approximately 3 percentage points. Aside from being a general equilibrium estimate, this figure expresses the response of value added (not profits), includes the potential effects of substitution into electronic payments technologies, and encompasses all sectors of the economy. For these three reasons, it is likely a lower bound on the size of the shock. Our point estimate however has a reasonable magnitude compared to theirs: for instance, assuming a labor share of 70% in retail, and no adjustment of labor or hours in the short-run, the implied decline in profit rates in retail using the 3% figure is $1/0.3 \times 3\% = 9\%$, or approximately a little over one third of our point estimate.

The magnitudes of the point estimates for the level and the slope of the switching frontier are difficult to interpret explicitly, but it is worth making two points about them. First, the point estimate of C is 0.063, with a normal 90% coverage interval of [0.056, 0.070]. Our findings therefore reject the null of no adoption

complementarities. Second, the point estimates imply that relative to cash, profits under the electronic technology are on average 3.0% lower if there are no other adopters, and 3.3% higher if there is full adoption. Together with other parameters, these differences imply that the equilibrium switching frontier is such that cash-based profits $M_{d,t}$ must fall by 12.6% in a district with $X_{d,t} = 0$ adoption, or about three standard deviations, in order for adoption to start. The estimated size of the shock substantially exceeds this threshold.

Finally, the point estimate of the rate of technology re-setting implies that, on average, firms receive the option to adjust their technological choice every 6.1 months, with the 90% coverage interval of the arrival rate corresponding to frequencies between 4.3 and 10.6 months. The estimate of k is fairly imprecise, but it implies that arrival rates higher than 3 months can be rejected at the 1% level. This relatively slow technological adjustment rate may reflect learning or cognitive costs associated with the use of the technology, which we leave unmodelled in the paper. Additionally, we can reject, at the 1% level, the null that $k > \theta$, so that at its point estimate, the model generates state-dependence in impulse responses.

Table 8 reports measures of goodness of fit. The first column reports the empirical value of the moment used in the estimation. The second column provides average values, standard deviations, and one-sided p-values obtained from $S_{CI} = 2000$ simulations of the model with structural parameters set to their estimated values, i.e. $\Theta = \hat{\Theta}$. We can reject equality of the empirical and simulated moments at the 1% for two of the eight moments, and overall, the over-identification test cannot reject the null that the model is correctly specified at the 1% level. The moment which the model has most difficulty matching is the interaction between the medium-run effect of the shock, and the pre-shock adoption level. This moment depends strongly on the variance of innovations to the idiosyncratic shocks to districts, which we primarily identify using the average squared residuals from equation (13). A higher variance of idiosyncratic innovations, in the model, will mask the dependence on initial conditions; but it may be necessary to match large squared residuals in empirical estimates of (13), which, themselves, may reflect unmodelled sources of variation in adoption rates. Otherwise, the model matches the empirical moments very closely, in particular with respect to the short- and long-run average adoption response, which are the two most precisely estimated moments in our data.

5.2 Quantitative implications

Next, we use the estimated model to construct the quantitative answer to three questions about the effects of the shock, and the role played by externalities in the adoption process.

5.2.1 How would adoption have responded, in the absence of externalities?

Figure 13 reports empirical and model-based paths of average adoption across districts, in the aftermath of the shock. At the point estimates reported in table 7, adoption rises by approximately 4p.p. by the end of December, and 7p.p. by the end of May, in line with the empirical estimates. (This is to be expected, since the short- and medium-run adoption increases are explicit targets of the estimation.) The figure also reports a counterfactual path of adoption rates, under the assumption that there are no complementarities, that is, when $C = 0$. With respect to the data, and to our baseline estimate, the adoption path is similar during the first three months, when the cash crunch is still ongoing. After that, it diverges from the data and from the model with complementarities, declining in the medium-run. The gap is fairly substantial: the predicted increase in adoption rates without complementarities would have been 4p.p. (or approximately 60%) lower than observed. Thus, the model attributes a important share of the response of adoption rates to complementarities.

5.2.2 What if the cash swap had been completed more quickly?

Figure 13 also reports counterfactual adoption paths which speak to the role of the size and persistence of the shock. We first construct adoption paths under the assumption that the 90% decay rate of the shock is two weeks, instead of three months; this captures a alternative world in which the cash swap would have been executed as rapidly as initially intended. Under this scenario, adoption would only have risen by approximately 2p.p., and the increase in the dispersion of adoption would have been negligible. Figure 13 also indicates that, if the shock had been smaller in magnitude — which could capture a situation in which only one denomination would have been replaced, for instance —, the long-run response would have been smaller. With a shock half as large, the average adoption rate only rises by approximately 4p.p., versus 7p.p. in the baseline case. The model thus suggests that the persistence and size of the cash crunch might have had substantial, though unintended, positive effects on adoption overall.

5.2.3 What sort of intervention maximizes long-run adoption?

We next use the model to ask whether a hypothetical planner could have achieved higher long-run changes in adoption rates by implementing the cash swap differently. In order to answer this question, we first define the cost of the cash swap as the present value of the decline in cash-based demand:

$$C(S, \theta) = \mathbb{E}_{t_0} \left[\sum_{n=0}^{+\infty} e^{-r\Delta n} \{M^c - M_{t_0+\Delta n}\} \right] = \frac{S}{1 - \exp(-(r + \theta))}. \quad (15)$$

We next consider the following maximization problem for the hypothetical planner:

$$\arg \max_{S, \theta} \quad \mathbb{E}_{t_0} [\Delta_{t_0} X_{d, t_0+T}] - \frac{g}{2} \text{var}_{t_0} [\Delta_{t_0} X_{d, t_0+T}] \quad \text{s.t. } C(S, \theta) \leq C(\hat{S}, \theta_0) \quad (16)$$

where \hat{S} is the value reported in table 7, $\theta_0 = \log(1 - 0.90)/(82/30)$ is the calibrated shock persistence, and g is an arbitrary positive number.

This is the problem facing the hypothetical planner who chooses the size and persistence of the shock to cash-based demand, aims to maximize average adoption at horizon $T = 3$ years, and possibly exhibits some aversion to dispersion in adoption rates (when $g > 0$). The aversion to dispersion could capture a preference of policymakers toward broad-based adoption. Furthermore, we assume this planner is constrained in the total cost of the intervention, and we use the empirically estimated cost of the demonetization shock as the maximum cost the planner can incur.

Table 9 reports the numerical solution to problem (16), under different values of g . Additionally, the first column reports the model estimates of the size and persistence of shocks, and the implied long-run first and second moments of the change in adoption rates.

Results for the first column, $g = 0$, show that the “constrained optimal” plan, for a planner that does not care about long-run dispersion in adoption rates across districts, involves choosing a shock that is more persistent but smaller than estimated than what the model estimates imply. Thus, the model indicates that, given the total cost of the intervention implied by the model estimates, a planner seeking to maximize long-run adoption could have done better than the observed outcome, by making the shock both more persistent and smaller. The difference with respect to the estimated shock, however, is not large (the shock half-life is approximately one month, instead of 0.8 month in the baseline case, and the shock would have been only 20% in size.)

A more persistent but smaller shock also leads to more dispersion in adoption rates in the long run. The intuition for this is that, with a smaller shock, a higher initial adoption rate is required for the district to enter the adoption region. The initial differences between districts are then exacerbated. As a result, long-run dispersion in the “constrained optimal” plan when $g = 0$ is higher than in the model estimates, as indicated in table 9.

However, as aversion to dispersion increases (that is, as g increases), the “constrained optimal plan” progressively involves smaller and more persistent shocks. As discussed in section 3, a more persistent shock (of a given size) tends to reduce long-run dispersion in outcomes, because it reduces the degree of state-dependence of adoption rates. In the limit where the shock is permanent, all districts whose initial adoption rates are sufficiently high that the shock triggers *some* adoption in the short-run, will also converge to full

adoption in the long-run. A planner who cares about dispersion thus has a motive to *further* increase the persistence of the intervention; at the point estimates of the model, this effect dominates the reduction in dispersion that a larger shock might generate. In particular, the “constrained optimal” plan with an aversion to dispersion of $\gamma = 0.5$ leads to comparable long-run dispersion than in the estimated model, but a lower average adoption rate.

Overall, while the size and persistence of the shock had positive effects on long-run adoption — as discussed above —, the model also suggests that if the objective of the policy had been to increase long-run adoption while minimizing the dispersion in outcomes across districts, a more persistent but smaller intervention would have been preferable. That said, long-run adoption gains under these alternative policies are relatively mild, in the order of 10 to 15% of the long-run adoption increase implied by the estimated model.

The analysis of this section has shown that the simple model of section 3 can account well for key moments of the data. The estimation of the model formally rejects the null of no complementarities, consistent with the reduced-form analysis of section 4. Additionally, counterfactuals suggest that complementarities account for 60% of the medium-run response of adoption, and that a smaller, but more persistent intervention may have led to a larger increase in long-run adoption rates, along with a lower long-run dispersion in adoption across districts.

6 Demonetization and real economic activity

Results from previous sections provide evidence that the Indian demonetization led to a widespread and persistent rise in electronic payments. Given the size and speed of these responses, one natural question is whether the rise in electronic money was indeed sufficient to shield the real economy from the cash crunch. In this section, we use household consumption data to explore this question. Overall, our evidence suggests that — while the shift towards electronic payment was not sufficient to completely replace cash — the presence of electronic payment options has helped consumers to limit the impact of the shock. Furthermore, in this section we provide some robustness exercises that are also relevant for the rest of the paper.

6.1 Empirical setting

In this Section, we examine how household consumption responded to the cash swap using the same identification strategy from Section 4. In other words, we compare behaviors across districts that were characterized by different exposure to chest banks before the demonetization. To measure the changes in consumption

behavior by Indian households, we use data from the Consumer Pyramids database maintained by the Center for Monitoring Indian Economy (CMIE).⁶¹

The data set provides a representative sample of Indian households, where households are selected to be representative of the population across 371 “homogeneous regions” across India. The survey has information on the monetary amount of the household expenses across different large categories and some other background information on the members of the households.⁶² Overall, the data quality is considered high, in particular since CMIE collects the data in person, using specialized workers. Each household is interviewed every four months and is asked about their consumption pattern in the preceding four months.⁶³

The main difference compared with the analyses in Section 4 is the timing. In the previous analyses, the district-level data were measured at monthly level. For these household data, the survey procedure is such that households belonging to different waves of interviews are asked about the same month at different points in time. Therefore, the reporting on November 2016 – the first month of the shock – is generally clustered together with a different group of months depending on the wave.⁶⁴ This feature is actually quite common among consumer surveys, and it is similar to the Consumer Expenditure Survey in the US.⁶⁵ Following the literature in this area (e.g. Parker et al. (2013)), we deal with this feature by organizing the data by event-time. In other words, for each household we aggregate data at the wave-level and we define the time of each wave relative to the wave containing November 2016.⁶⁶

With this data set of about 95,000 households, we then estimate the following household-level difference-in-difference model:⁶⁷

$$\log(y_{h,d,t}) = \alpha_t + \alpha_h + \delta_t (\text{Exposure}_d \times \mathbf{1}_{\{t \geq t_0\}}) + \Gamma'_t Y_{h,d} + \epsilon_{h,d,t}, \quad (17)$$

where $y_{h,d,t}$ are consumption measures for household h in district d and survey-time t , α_t and α_h are event-time and household fixed effects, Exposure_d is the district’s exposure as described in Section 3, which is

⁶¹This data set has two crucial advantages relative to the widely used National Sample Survey (NSS), which is a consumption survey conducted by the central government agencies. First, the NSS is not available for the period of interest, as it was ran for the last time in 2011. Second, the NSS is a repeated cross-section of households, while CMIE data is a panel data set.

⁶²The expense categories include food, intoxicants, clothing and footwear, cosmetics and toiletries, restaurants, recreation, transport, power and fuel, communication and information services, health, education, bills and rents, appliances, equal monthly installments (EMIs), and others.

⁶³Thus, about 39,500 households are surveyed every month.

⁶⁴For example, 25% percent of households will be asked about August-November 2016 consumption in December 2016, 25% percent will be asked about September-December 2016 consumption in January 2017 and so on. Thus, November 2016 consumption will be recorded with other months depending on the month it was surveyed between December 2016-March 2017.

⁶⁵The main difference is that the Consumer Expenditure Survey is run every three months rather than four months.

⁶⁶Therefore, the time in the panel is the one for the wave in which a household was interviewed about November, and it is zero for the wave that happened four months before the one that includes November 2016 and one for the one that happened four months after.

⁶⁷We only consider households for which the age of the head of household is between 18 and 75 years as of September 2016. We then only consider households with non-missing information between June 2016 and March 2017, giving us a balanced panel of about 95,000 households.

interacted with dummies for the survey-time post-demonetization, and $Y_{h,d}$ are controls, which are either at district or individual level. For controls in the regression, we use the same district-level covariates as in the previous set of analyses along with the addition of household-level controls including the age of the head of the household and log of household income, both measured as in the last survey before the shock. As usual, standard errors are clustered at district level, which is the level of the treatment.

6.2 Main results

Table 6 shows the results for consumption responses based on exposure to the shock. Column (1) shows that relative to the pre-period, total consumption was cut more for households located in the highly affected district. The effect is sizable: consider that a one-standard deviation increase in the chest bank score corresponds to about a 3.6% relative decline in total consumption. The same holds when using a dichotomous version of the shock: in this case, the highly affected households (top quartile) saw a relative drop of about 5.7%.

Importantly, the impact of the shock was temporary. Looking at the interaction between the treatment and dummies identifying the next 3 waves in which the household was interviewed, we consistently find a small and nonsignificant coefficient. If anything, the coefficient is positive during some of the post-periods, but generally this result is nonsignificant. This effect suggests that the cash contraction only significantly impacted household behavior during the months immediately after the demonetization and did not lead to a permanent change in consumption behavior. This evidence is consistent with the idea that the shock was really only binding between November and January.⁶⁸

To understand better the effect on consumption dynamics, we repeat the same analysis by dividing aggregate consumption into finer categories (Table D.8). As a first step, we divide consumption into necessary and unnecessary consumption. With this measure, we want to identify the subset of the consumption basket that is harder to cut for households, and for which we therefore expect to see a lower response. Specifically, we consider necessary all consumption expenses for food, rent and bills, and utilities (power and gas). Our finding is that - while consumption was cut across the two baskets of goods - the effect on unnecessary was economically larger (about 22% higher). The same difference also holds when looking using a dichotomous treatment (Appendix Table D.9). In this case, highly affected households cut necessary consumption by 4%, while unnecessary consumption by about 8%.

Importantly, this last result does not depend on the way we categorize consumption as necessary and unnecessary. In Columns (3)-(5) of Table D.8, we consider three consumption categories: rent and bills,

⁶⁸Because of the data structure, the timing of the second wave is different across households, depending on the group in which they belong. However, for three-quarter of the sample, the second wave starts on or after January 2017, which is the month in which we saw a net influx of cash back in the economy.

food, and recreational expenses. For the first group - rent and bills - we find essentially no effect of the demonetization. For food, the effect is still negative and significant. In particular, a one standard-deviation increase in exposure led to about 3% decline in food expenditure. However, this effect on food dwarfs in comparison to the cut on recreational expenses. For this category, we find that a standard-deviation increases led to more than a 15% cut in consumption.

While this evidence confirms that the rise in electronic payment was unable to undo the effects of the cash contraction, it may still be the case that electronic payments helped to partially limit the impact of the shock. To test this hypothesis, we examine the responsiveness to the shock across areas characterized by different levels of penetration of electronic payments in the pre-shock period. In particular, we focus on the penetration of debit cards, which we proxy by the number of ATMs per million people in a district.⁶⁹ Our focus on traditional electronic payment is motivated by its relative size. In fact, debit cards represent the largest share of electronic transaction in India. Furthermore, while the issuance of new debit cards was overall modest, the demonetization led to an increase in the amount of transactions, suggesting that debit cards were indeed used as a way to replace cash during the shock period.

The results of this analysis are presented in Table ???. The key parameter in these regressions is the triple interaction between the time dummies, the measure of exposure to the shock, and a dummy that takes value one for districts that have an above-median number of ATMs per one million people. We repeat the same analysis using both the continuous (odd columns) and dichotomous (even columns) versions of the shock. Looking at total consumption (columns 1 and 2), we find consistently that the effect of the cash contraction was smaller in districts with a high penetration in electronic payments. Depending on the specification, districts with high penetration experienced a contraction in total consumption that is between 60% and 90% smaller than in low penetration areas.

The access to electronic payments helped to reduce the impact of the shock in necessary consumption (columns 3 and 4),⁷⁰ the impact in explaining the effect for unnecessary consumption was minimal (columns 5 and 6). This heterogeneity between types of consumption is consistent with both demand and supply mechanisms. On the one hand, consumers facing a scarce access to electronic payments may be more likely to allocate a larger share of their electronic money to necessary consumption. On the other hand, for necessary consumption – in particular food – consumers are more likely to face the option to trade with retailers that are larger in size (e.g. grocery chains) relative to unnecessary consumption (e.g. restaurants).

These results show that the cash contraction had a negative effect on individual consumption. However,

⁶⁹The underlying assumption is that districts with a high number of ATMs per person will also be characterized by the highest concentration of debit cards and POS machines. We focus on ATM rather than directly on cards or POS, since we cannot directly measure the number of debit cards or POS machines at the district level, but only in aggregate.

⁷⁰In an unreported regression, we find that this result is the same when looking at food expenditure, which is indeed an important part of our definition of necessary consumption.

the impact of the shock was indeed smaller than one might have expected ex ante. In particular, the negative effects were somehow limited to the most acute period of the demonetization. Furthermore, the cut was larger for less necessary goods, like recreational expenses, and much more limited for food expense. Building on these patterns, we also show that the presence of a developed electronic payment infrastructure in a local market explains part of the variation in the response to the shock in the local market. This evidence suggests that – while electronic money was not sufficient to completely shield the economy from the contraction – its presence may have played a role in limiting the costs of the demonetization.

6.3 Robustness

In this Section, we present a set of robustness tests that helps validate the causal interpretation of the results presented earlier. Together with the discussion in Section 4, these tests provide support for the idea that district’s exposure to chest banks represents a credible empirical method to explore the effect of the demonetization.

In Figure D.12, we confirm that the consumption result is not driven by differences in pre-trend between affected districts. Echoing the results on electronic payments in Section 4, we find that the exposure measure constructed based on chest banks does not appear to be correlated with differential trends in consumption before the shock. However, it does predict a different response during the demonetization — as previously discussed.⁷¹

One residual concern is that districts with high exposure to chest banks are regions that are particularly sensitive to business cycle fluctuations. The pre-trend analysis partially helps with this concern, but it cannot rule this out completely because it focuses on one specific point in time. Therefore, to bolster our identification further, we construct a large set of placebo tests, in which we repeat our main analysis centering it in periods in which there was no contraction in cash. In particular, to keep our approach general enough, we consider placebo shocks happening every month between February 2015 and February 2016. We then replicate our main specification, testing for the presence of a differential response across households in the wave of the placebo shock relative to the previous one.⁷²

The results of this set of placebo tests are reported in Figure D.4. The general finding is that — in normal times — there is essentially no statistical difference in the change in total consumption between households

⁷¹This analysis shows a positive and borderline significant effect on consumption two quarters after the demonetization. One interpretation is that households have shifted some consumption in the future. Consistent with this interpretation, we actually find that the effect is driven entirely by unnecessary consumption, which is a category that also contains durable expenditure. However, we also want to point out that this positive result is statistically weak and it does not replicate using alternative treatment specifications (e.g. using top quartile).

⁷²In our main result, there is essentially no difference when we compare the effect on the previous wave - as in Figure D.12 - or the average of the previous three waves, like in Table 6. Here we choose to compare to the previous wave because this allows us to go further back in time with the placebo.

in districts with different chest bank exposure. Together with the pre-trend analysis, this test excludes the concern that differential exposure to business cycles may explain our results. More broadly, this test provides new evidence on the validity of our empirical specification.

7 Conclusion

In this paper, we study adoption dynamics for a technology characterized by externalities. In particular our main focus is on electronic payment systems and we use the Indian demonetization of 2016 as a laboratory to study how a large but temporary aggregate shock can affect adoption in this context. We show that the shock led to a permanent increase in the adoption of electronic-wallet technologies by firms. Our results support the view that, beyond fixed adoption costs, the event succeeded in fostering large scale adoption of electronic payments due to complementarities. In particular, the shock served as a coordinating device that allowed firms to overcome coordination frictions in the adoption of the technology.

We begin by documenting a large and persistent increase in the aggregate adoption of electronic wallet technologies by firms in India following the demonetization. Furthermore, we find similar effects on more traditional forms of electronic payment. However, consistent with the idea that traditional technologies are characterized with higher adoption costs than fintech, we document that in large part the effect on electronic payments is driven by the intensive margin, while the extensive margin effect (new cards or POS) is minimal.

Next, we explain these findings through the lens of a dynamic model of technology adoption with positive externalities. The model rationalizes the permanent increase in adoption (even though the shock was transitory) and highlights the importance of complementarities in explaining this persistence. At the same time, a key result from the model is state-dependence: we show that the adoption response in a model with complementarities and temporary shocks is not necessarily uniform. In particular, the initial strength of complementarities - as proxied in the model by the initial number of users - positively predicts the response in the long-run. This long-run state-dependence disappears when the shock is more persistent (or at the limit permanent). This result highlights the trade-off between the duration of the shock and its distributional effects. Assuming that a policy-maker prefers a short-lived intervention to a longer one, the model suggests that while the temporary shock can be successful in increasing overall adoption, it may increase dispersion in adoption.

As a first step, we empirically test the predictions of the model using disaggregated data on electronic payment. As a first step, we develop a novel identification strategy based on the heterogeneity in the presence of chest banks across Indian districts to estimate the causal impact of the cash contraction on adoption. We confirm that the shock also had a persistent effect on the adoption of the technology across districts. In part,

this permanent increase in adoption is driven by an increase in the entry of new firms into the platform. In line with the model with complementarities, we find that this difference in entry persisted even after the shock dissipated.

Next, we show that patterns of adoption are consistent with the presence of state-dependence. In particular, using three separate tests, we document that the increase in adoption appears to be positively affected by the initial strength of complementarities. First, we show that districts with a higher level of early adoption on average increased technology adoption more. Second, we show that the propagation of electronic payment technologies was stronger in areas that were closer to the centers in which electronic payments were already widely used in the pre-shock period. Third, we show that a firm-level decision to use the technology is influenced by the recent behavior of other firms in the same industry and area.

We go one step further, and use the model to quantify the contribution of externalities in the adoption response to the demonetization. We estimate the model using district-level data on adoption rates, and use the estimated model to produce counterfactuals, which show that adoption would have been about 60% lower in the absence of complementarities.

Finally, we confirm that the large increase in electronic payments was overall insufficient to limit the impact of the cash contraction. Consistent with this hypothesis, we find that the cash contraction caused a sizable negative effect on consumption by Indian households. However, access to electronic payment technologies in the local area appears to help households to smooth the negative impact of the cash contraction.

Future work should extend this paper in two dimensions. First, new research should test the basic model presented in this paper across different policy interventions and technologies. While the adoption of financial technologies suits particularly well this setting, the model on itself can be used to also examine adoption behavior of any technology characterized by externalities. In particular, the model may provide a good conceptual framework for empirical work in this area. Second, future work should study the strategic change in firms' behavior in response to the adoption of electronic payments. In this area, the recent paper by [Higgins \(2019\)](#) finds that the adoption of electronic payments may affect the consumption patterns of households. However, less is known regarding how firms' activities is affected by switching to electronic payments.

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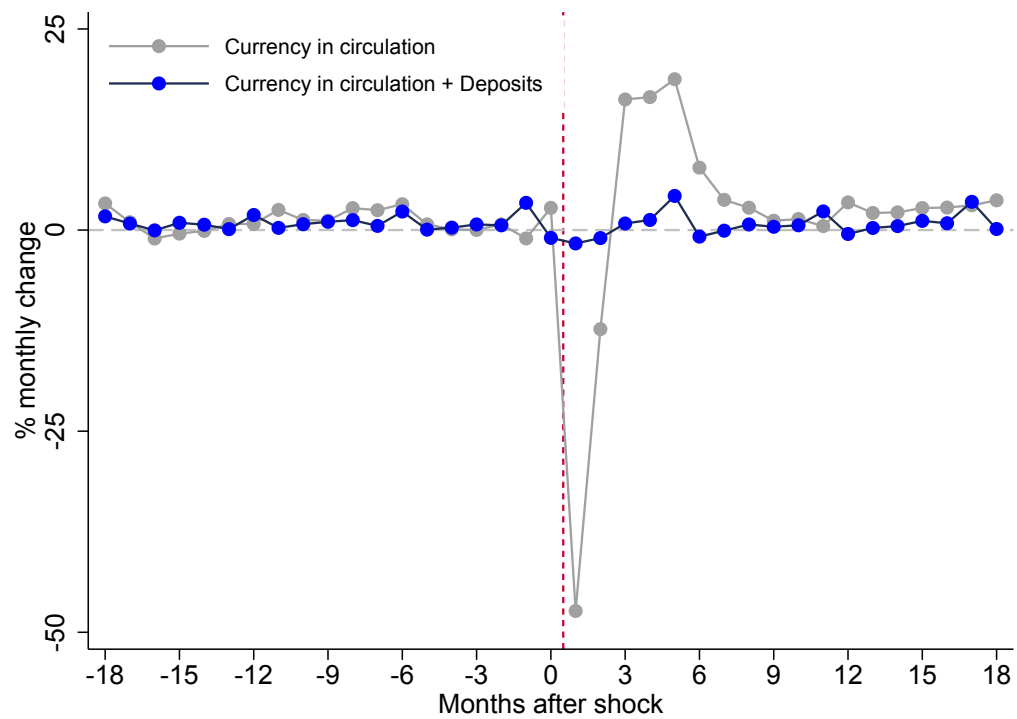
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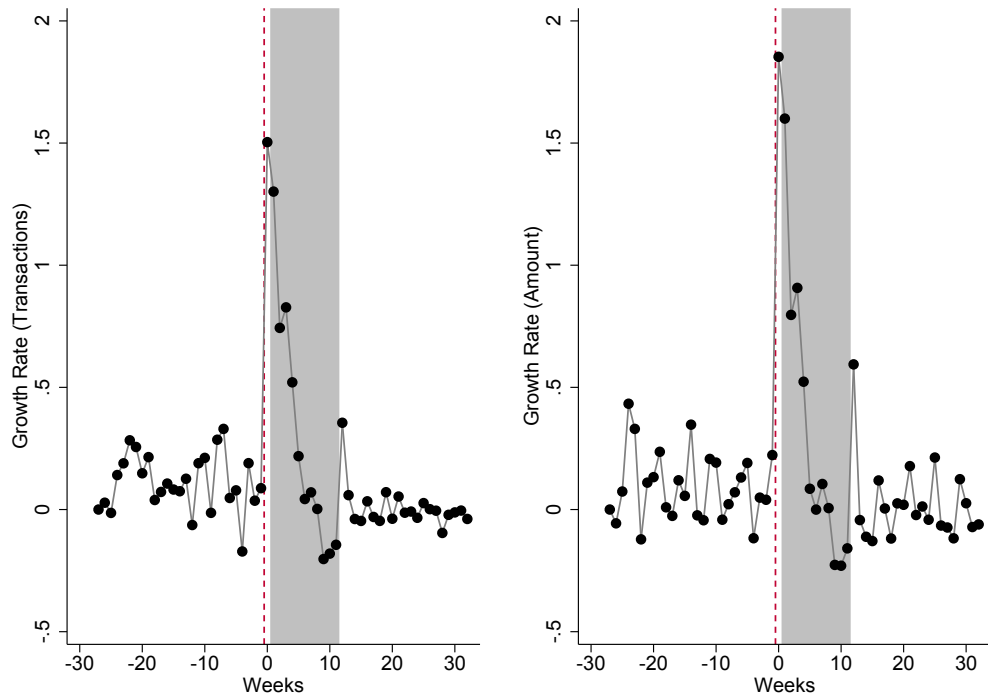
A Figures and tables

Figure 2: Change in nominal value of currency in circulation



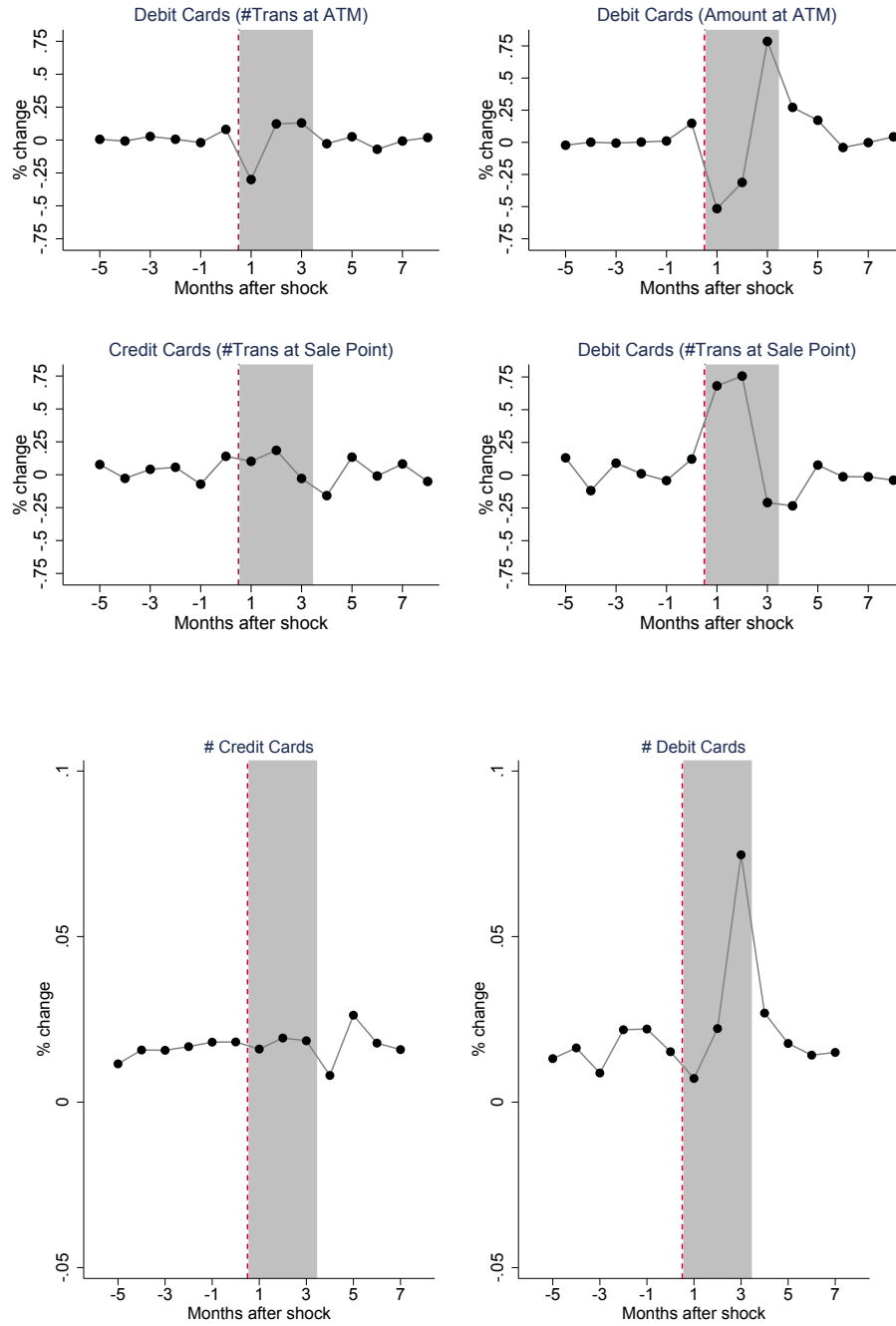
Notes: The figure shows the change in the nominal value of the stock of currency in circulation (in grey) and change in the value of the total money supply (in blue) in India. Month 0 is the month of October 2016; the figures are end-of-month estimates. Source: Reserve Bank of India.

Figure 3: Amount and Transaction Growth on Mobile Payment Platform



Notes: Week-on-week growth rate in the number of transactions (left panel) and amounts (right panel) on the electronic wallet platform. The dashed red line indicates the week of November 8th, 2016. See main text for a discussion of data sources.

Figure 4: Changes across alternate electronic payment systems



Notes: Change in the use of other electronic payment systems for credit cards, debit cards and POS (point of sale machines) around the period of the shock. The top panel reports the measures of intensive margin use, and the bottom panel reports the measures of adoption. All the data are monthly and aggregated at the national level. The x -axis represents the month, where October 2016 is normalized to be zero. Source: Reserve Bank of India.

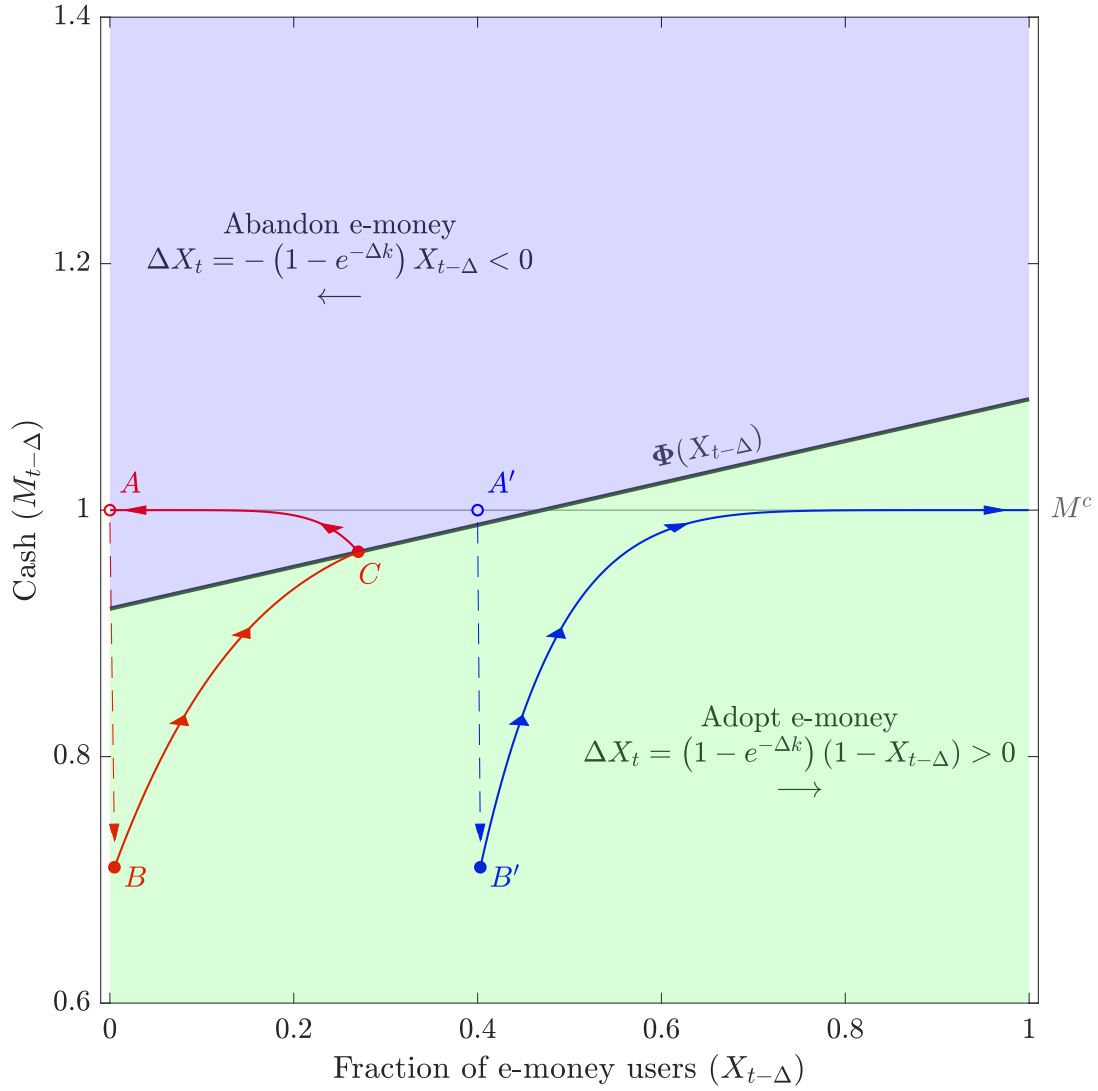


Figure 5: Adoption dynamics in response to a large decline in M_t in the complementarities model ($C > 0$ and $\kappa = 0$). The model illustrated here corresponds to the case $\theta > k$ (the shock is transitory relative to the adjustment speed of firms). The red line shows the path of a district that starts with a low adoption level $X_{d,0} = 0$. The blue line shows the path of a district that starts with a high adoption level, $X_{d,0} = 0.4$. The paths are constructed assuming that each district receives no other shock than the initial decline in M_t , i.e. that $\epsilon_t = 0$ for all $t > 0$.

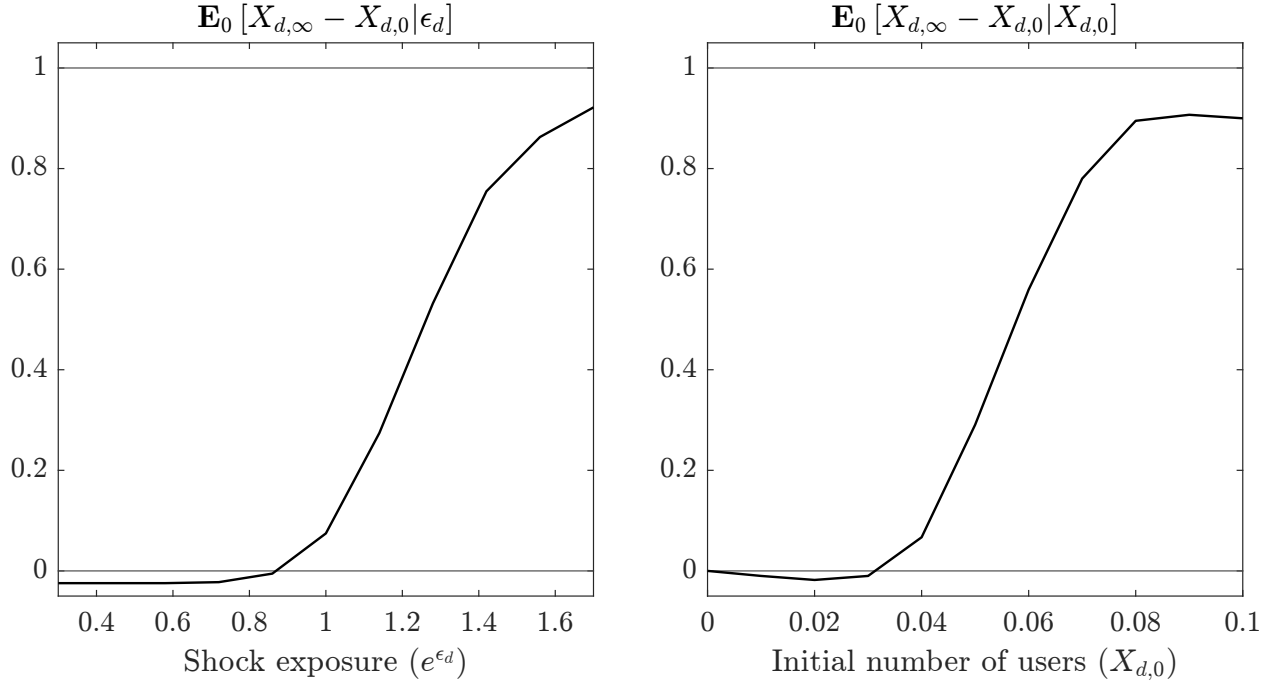


Figure 6: Conditional impulse responses in the complementarities model ($C > 0$ and $\kappa = 0$). These impulse responses are generated from the same type of simulations as in figure D.3. The left column reports the relationship between the district's exposure to the shock, proxied by e^{ϵ_d} (with a value of 1 indicating an average exposure to the shock), and the long-run change in the number of users after the shock. The right column reports the relationship between the initial number of users, $X_{d,0}$, and the long-run change in the number of users after the shock. The long-run number of users in the left panel is defined as $E_0[X_{d,\infty} - X_{d,0} | \epsilon_d] = \lim_{t \rightarrow +\infty} E_0[X_{d,t} - X_{d,0} | \epsilon_d]$ (and similarly for the right panel). For both columns, in each district, the adoption path is constructed by averaging across 10^3 draws. The limit as $t \rightarrow \infty$ is obtained by simulating the response of each district for five years and using the end-of-simulation values.

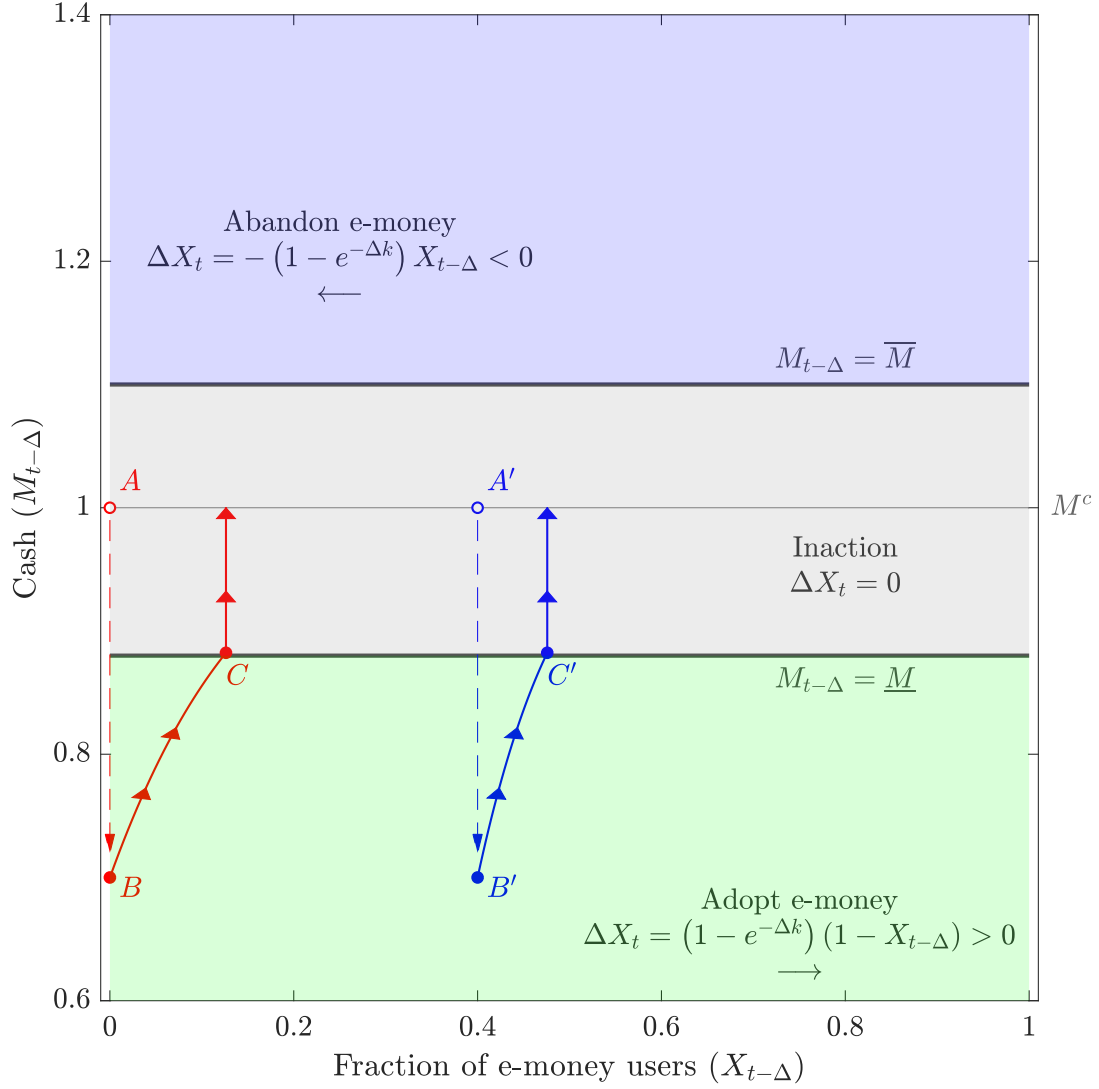
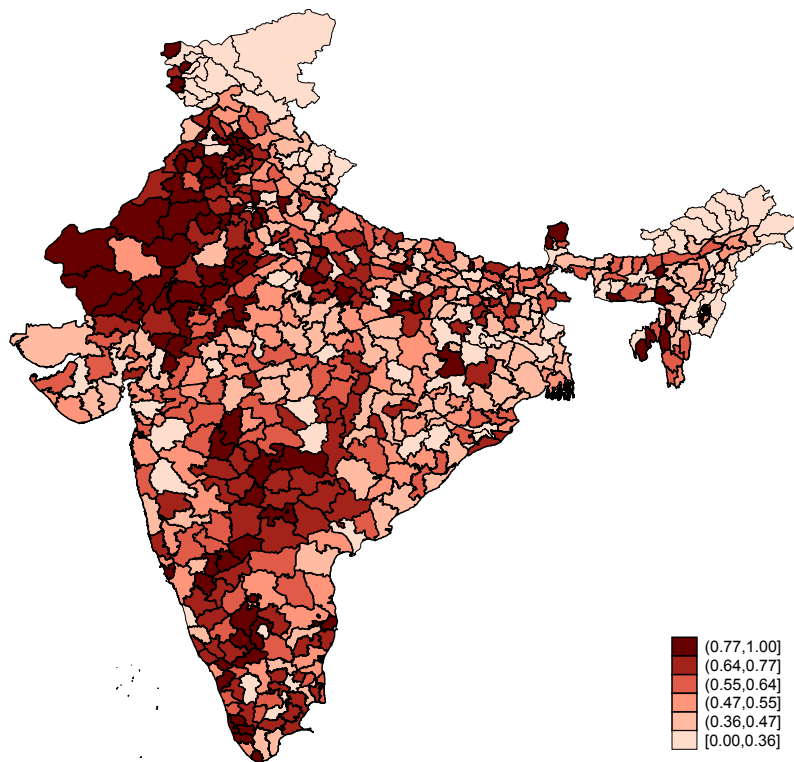


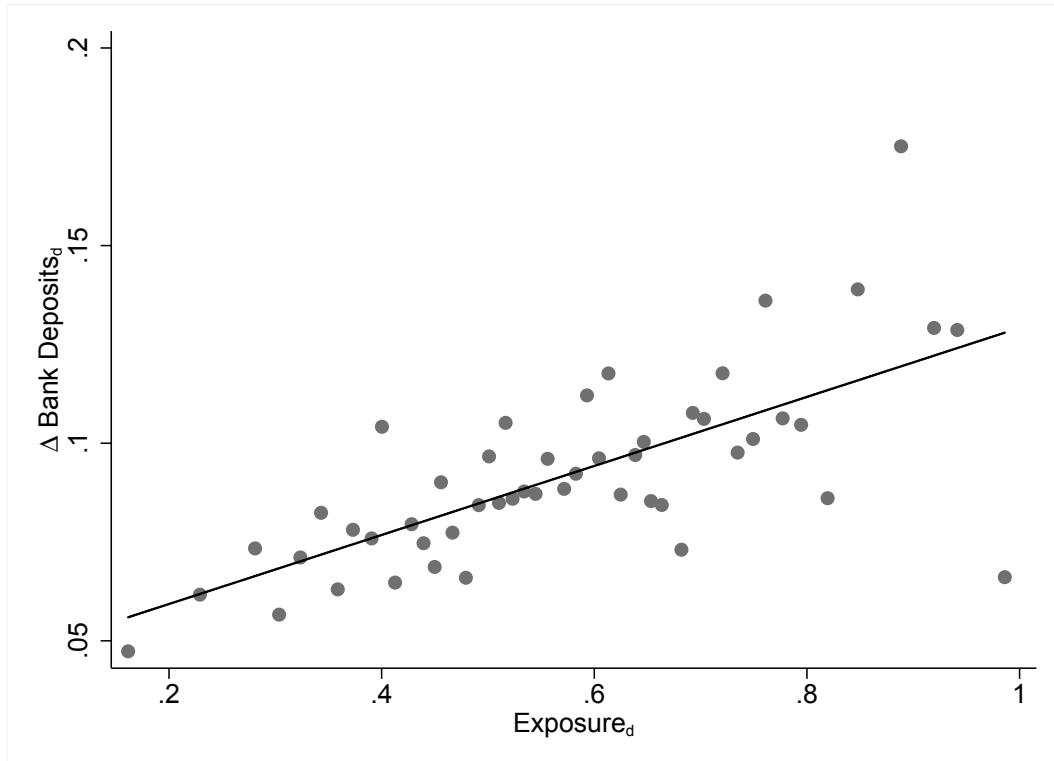
Figure 7: Adoption dynamics in response to a large decline in M_t in the fixed cost model ($C = 0$ and $\kappa > 0$). The red line shows the path of a district that starts with a low adoption level $X_{d,0} = 0$. The blue line shows the path of a district that starts with a high adoption level, $X_{d,0} = 0.4$. The paths are constructed assuming that each district receives no other shock than the initial decline in M_t , i.e. that $\epsilon_t = 0$ for all $t > 0$.

Figure 8: Map of the Distribution of Exposure_d



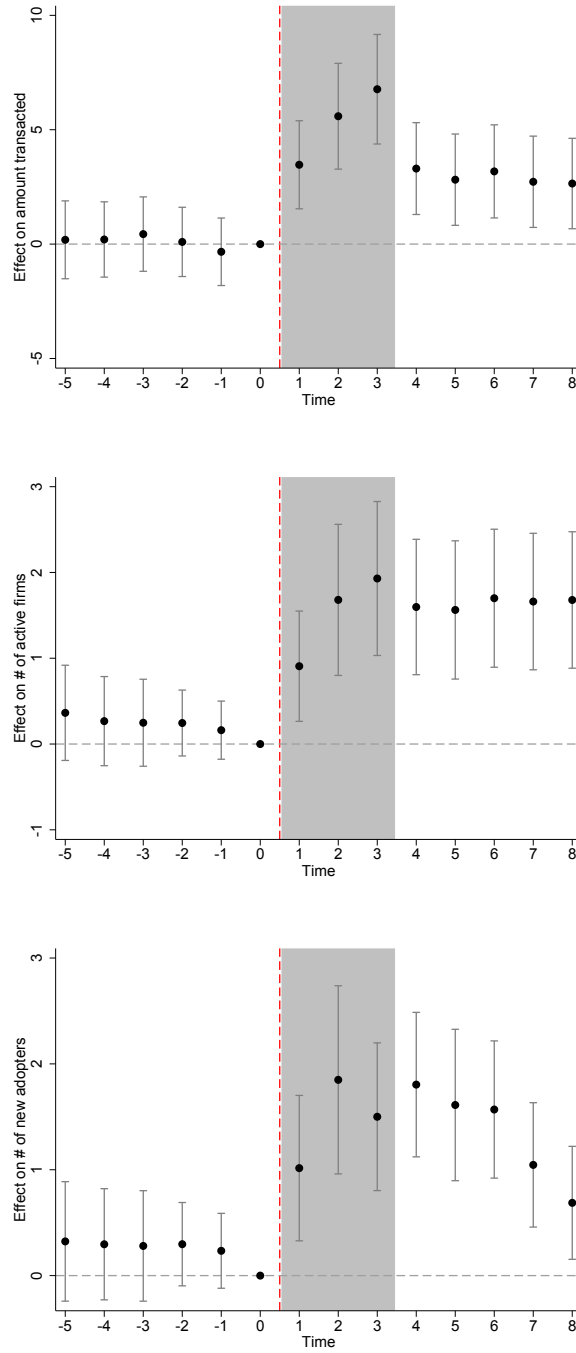
Notes: The figure maps the distribution of Exposure_d (as described in Section 2) across Indian districts. Source: Reserve Bank of India

Figure 9: Relation between Exposure and 2016 Q4 deposit growth



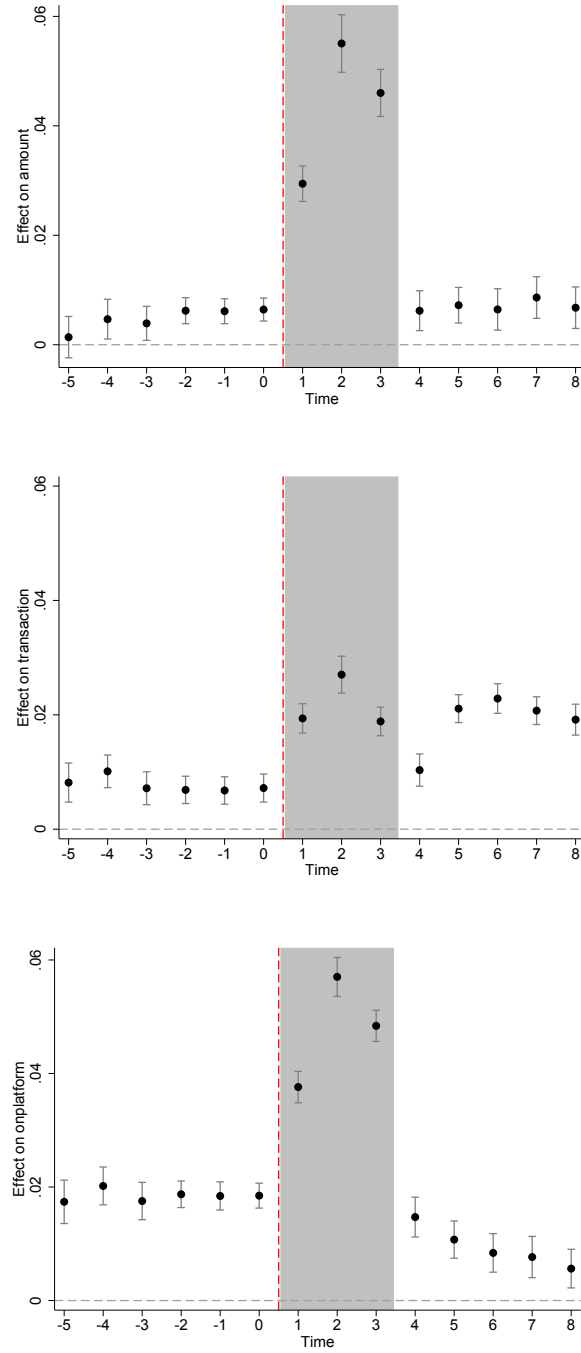
Notes: The figure shows the relation between our measure of Exposure_d (as described in Section 2) and the change in bank deposits in the district between September 30, 2016 and December 31, 2016 *i.e.* during the quarter of demonetization. Source: Reserve Bank of India.

Figure 10: District adoption dynamics in electronic payments data based on exposure to shock



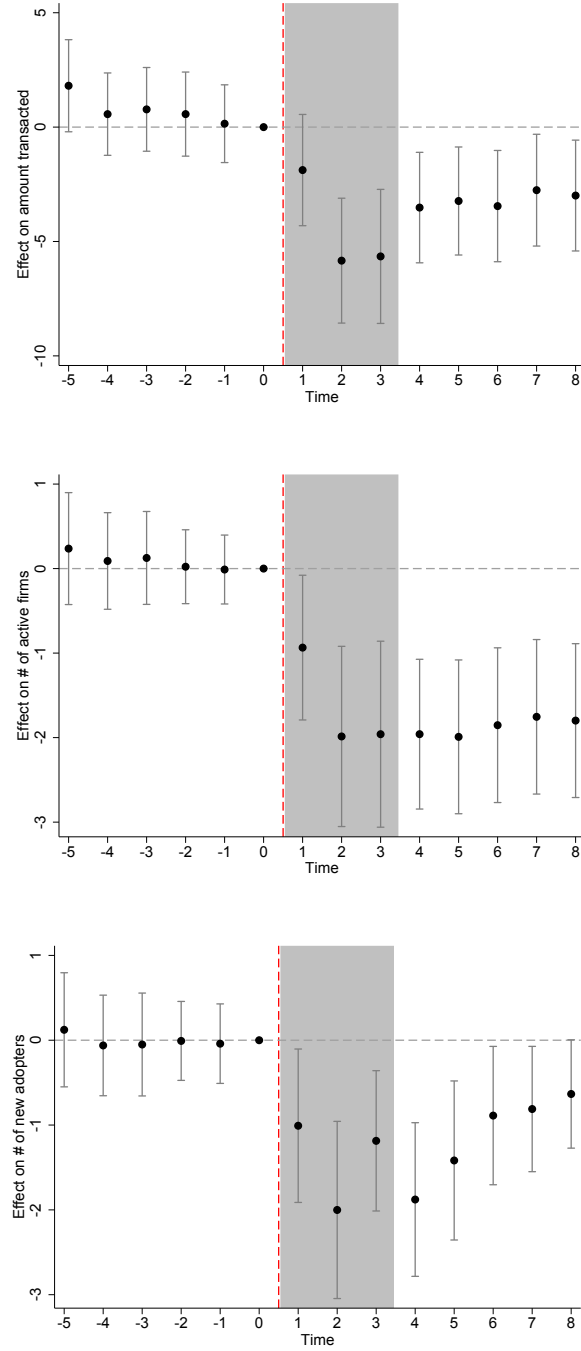
Notes: The figure plots the dynamic treatment effects of the demonetization shock on technology adoption of electronic payment systems. The graphs report the coefficients δ_t from specification 8; the top panel reports the effects for the total amount of transactions (in logs), the middle panel reports the effects for the total number of active firms on the platform (in logs), and the bottom panel reports the effect for the total number of new firms on the platform (in logs). The x -axis represents the month, where October 2016 is normalized to be zero. 95% confidence intervals are represented with the vertical lines; standard errors are clustered at the district level.

Figure 11: Firm adoption dynamics in electronic payments data based on existing adopters



Notes: The figure plots month-by-month estimates of the dependence of firm-level adoption rates on the share of other adopters in the industry/pincode. The specification we estimate is a version of equation 12 in which each coefficient is interacted with a weekly dummy; we reported the monthly estimates of the coefficient γ . The top panel reports the effects when x is the total amount of transactions, the middle panel reports the effects when x is the total number of transactions, and the bottom panel reports the effects when x is a dummy for whether the firm used the platform over the past week. 95% confidence intervals are represented with the vertical lines; standard errors are clustered at the pincode level.

Figure 12: District adoption dynamics in electronic payments data based on distance to electronic hub



Notes: The figure plots the dynamic effects of adoption across districts based on a district's initial adoption rates as proxied by the distance of that district to the closest district with more than 500 active firms before demonetization. The specification we estimate δ_t in the dynamic version of equation 9. The top panel reports the effects for the total amount of transactions (in logs), the middle panel looks at the total number of firms, while the bottom panel reports the effects for the total number of new firms transacting on the platform (in logs). The x -axis represents month, where October 2016 is normalized to be zero. 95% confidence intervals are represented with the vertical lines; standard errors are clustered at the district level.

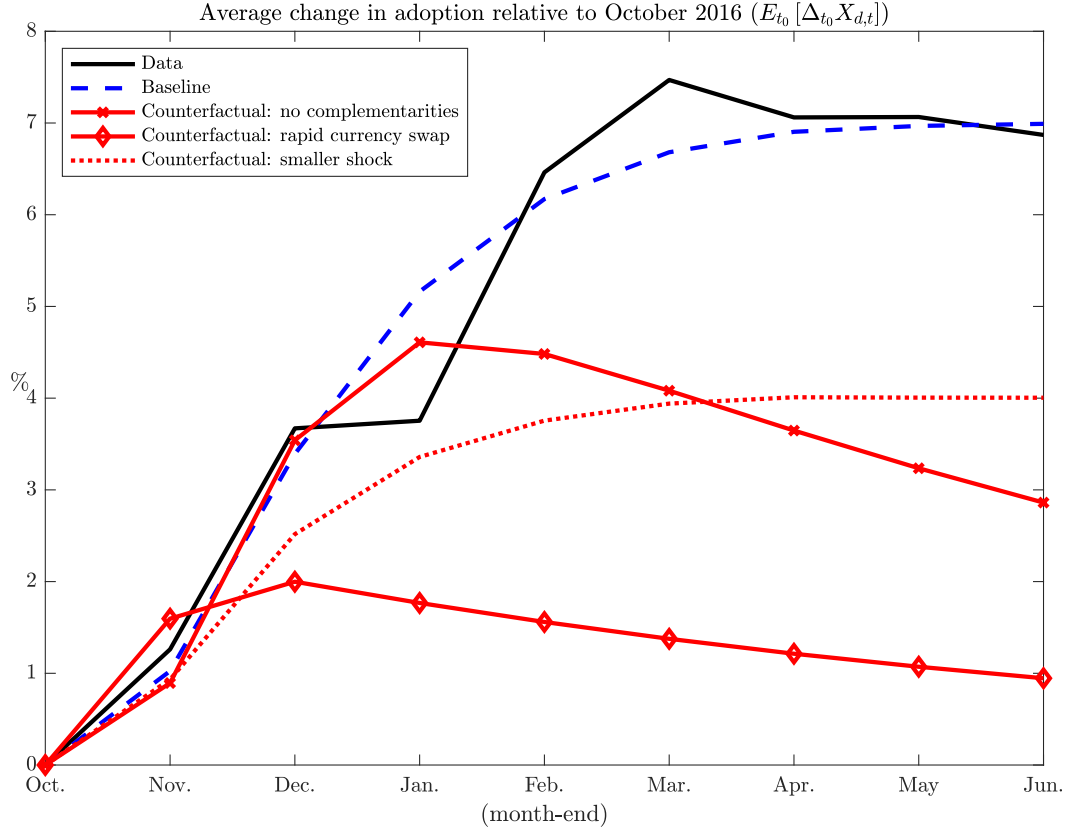


Figure 13: Counterfactual paths of average adoption rates across districts. The black solid line reports the empirical change in average adoption rates across districts. The other lines report average changes in adoption rates constructed using $S = 100$ simulations from the model, each of a dataset of the same size as the actual data. The dashed blue line is the change in adoption rate obtained from the model evaluated at the point estimates reported in table 7. The solid crossed red line is the average change in adoption rate in the absence of complementarities, assuming that the switching frontier (which is flat without externalities) has the same level as the switching frontier with externalities when adoption is 0. The solid diamond red line is the change in adoption rate when $\theta = 4.6$, corresponding to a 90 – % decay time of 15 days. The dotted red line is the change in adoption rate when the shock has half the initial size as that estimated in table 7.

Table 2: Exposure_d and district characteristics (Balance Test)

	(1)	(2)	(3)	(4)	(5)
Dependent variable:	mean	univariate OLS		baseline controls	
		coeff.	R ²	coeff.	R ²
Log(Pre Deposits)	11.083 (0.048)	-1.290*** (0.273)	0.054		
% villages with ATM	0.036 (0.004)	0.090*** (0.023)	0.040		
# Bank Branches per 1000's	0.047 (0.002)	0.002 (0.012)	0.000	0.015 (0.012)	0.234
# Agri Credit Societies per 1000's	0.045 (0.004)	-0.016 (0.027)	0.001	0.016 (0.022)	0.062
% villages with banks	0.085 (0.006)	0.131*** (0.036)	0.033	0.058 (0.036)	0.580
Log(Population)	14.376 (0.035)	-0.501** (0.208)	0.015	0.304 (0.199)	0.481
Literacy rate	0.622 (0.005)	-0.029 (0.025)	0.003	-0.001 (0.025)	0.227
Sex Ratio	0.946 (0.003)	0.008 (0.015)	0.001	-0.009 (0.017)	0.063
Growth Rate	0.208 (0.016)	-0.219 (0.139)	0.014	-0.232 (0.171)	0.021
Working Pop./Total Pop.	0.410 (0.003)	0.026 (0.016)	0.005	0.010 (0.017)	0.075
Distance to State Capital(kms.)	0.215 (0.006)	0.035 (0.032)	0.002	0.026 (0.032)	0.016
Rural Pop./Total Pop.	0.746 (0.008)	0.170*** (0.047)	0.034	0.046 (0.039)	0.464

Notes: The table tests for differences in observable district-characteristics and Exposure_d. Column 1 reports the mean of the district-characteristics. The treatment variables is our measure of Exposure_d as described in Section 2. Columns (2) & (3) report the coefficient of the univariate OLS regression of each variable on the treatment variable. Columns (4) & (5) report the coefficients after controlling for the pre-demonetization bank deposits in the districts (in logs) and share of villages with an ATM. Robust standard errors are reported in parentheses. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table 3: Exposure_{*d*} and adoption of digital wallet

	log(amount)	log(# users)	log(# switchers)
	(1)	(2)	(3)
(Exposure) _{<i>d</i>} × 1 (<i>t</i> ≥ <i>t</i> ₀)	3.134*** [0.884]	1.054** [0.423]	0.851*** [0.326]
Observations	6,846	6,846	6,552
R-squared	0.849	0.868	0.830
District f.e.	✓	✓	✓
Month f.e.	✓	✓	✓
District Controls × Month f.e.	✓	✓	✓

Notes: Difference-in-differences estimates of the effect of the shock on the adoption of digital wallet. The estimated specification is equation (7). In Column (1), the dependent variable is the log of the total amount (in Rs.) of transactions carried out using digital wallet in district *d* during month *t*; in Column (2), the dependent variable is the log of the total number of active retailers using a digital wallet in district *d* during month *t*; in Column (3), the dependent variable is the log of the total number of new retailers joining the digital wallet in district *d* during month *t*. District controls include (log) pre-shock banking deposits, share of villages with ATM facilities, share of villages with banking facility, share of rural population and level of population in the district. Standard errors clustered at the district level are reported in parentheses. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table 4: Firm adoption based on existing adoption rate in electronic payments data

	(1)	(2)	(3)	(4)
$x_{i,k,p,t} = \log(\text{amount})_{i,k,p,t}$				
$x_{i,k,p,t-1}$	0.528*** (0.005)	0.437*** (0.004)	0.369*** (0.004)	0.358*** (0.004)
$X_{k,p,t-1}$	0.090*** (0.003)	0.155*** (0.001)	0.032*** (0.001)	0.015*** (0.001)
R ²	0.365	0.404	0.455	0.460
$x_{i,k,p,t} = \log(\# \text{ transactions})_{i,k,p,t}$				
$x_{i,k,p,t-1}$	0.707*** (0.005)	0.617*** (0.005)	0.593*** (0.005)	0.577*** (0.005)
$X_{k,p,t-1}$	0.032*** (0.002)	0.062*** (0.002)	0.041*** (0.001)	0.017*** (0.001)
R ²	0.549	0.574	0.601	0.606
$x_{i,k,p,t} = \mathbf{1}\{\text{On platform}\}_{i,k,p,t}$				
$x_{i,k,p,t-1}$	0.509*** (0.005)	0.404*** (0.004)	0.334*** (0.003)	0.323*** (0.003)
$X_{k,p,t-1}$	0.046*** (0.004)	0.097*** (0.003)	0.038*** (0.002)	0.022*** (0.001)
R ²	0.341	0.387	0.443	0.448
Firm F.E.		✓	✓	✓
Pincode \times Week F.E.			✓	✓
Industry \times Week F.E.				✓
Observations	11,750,558	11,750,558	11,541,757	11,541,757

Notes: The table reports estimates of the dependence of firm-level adoption rates on the share of other adopters in the industry/pincode. The specification we estimate is a version of equation 12 in which each coefficient is interacted with a weekly dummy; we reported the estimates of the coefficient γ . The top panel reports effects when x is the total value of the transactions, the middle panel reports the effects when x is the total number of transactions, and the bottom panel reports the effects when x is a dummy for whether the firm used the platform over the past week. Standard errors clustered at pincode level are reported in parentheses. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table 5: District adoption rate of digital wallet based on distance to the hubs

	log(amount)		log(# users)		log(# switchers)	
	(1)	(2)	(3)	(4)	(5)	(6)
$(\text{Distance to hub})_d \times \mathbf{1}(t \geq t_0)$	-5.098*** [0.936]	-3.958*** [1.190]	-2.233*** [0.468]	-1.724*** [0.497]	-1.613*** [0.361]	-1.100*** [0.387]
Observations	6,846	6,846	6,846	6,846	6,846	6,846
R-squared	0.852	0.886	0.871	0.912	0.821	0.871
District Controls \times Month f.e.	✓	✓	✓	✓	✓	✓
State \times Month f.e.		✓		✓		✓

Notes: Difference-in-differences estimate of the effect of initial conditions, using the distance to the nearest hub (defined as districts with more than 500 retailers in September 2016) as a proxy for the initial share of adopters. The specification estimated is equation 10. In Columns (1)-(2), the dependent variable is the log of the total amount (in Rs.) of transactions carried out using a digital wallet in district d during month t ; in Columns (3)-(4), the dependent variable is the log of the total number of active retailers using a digital wallet in district d during month t ; in Columns (5)-(6), the dependent variable is the log of the total number of new retailers joining the digital wallet in district d during month t . District-level controls include (log) pre-shock banking deposits, share of villages with ATM facilities, share of villages with banking facility, share of rural population, level of population, distance to state capital and employment rate in the district. Standard errors clustered at district level are reported in parentheses. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table 6: Consumption responses based on exposure to the shock

Exposure _d :	log(Expense _{Total})	
	Continuous measure	Top 25%
	(1)	(2)
(Exposure) _d × 1(<i>t</i> = <i>t</i> ₁)	-0.199*** (0.0637)	-0.0577** (0.0234)
(Exposure) _d × 1(<i>t</i> = <i>t</i> ₂)	-0.0337 (0.0815)	-0.0199 (0.0296)
(Exposure) _d × 1(<i>t</i> = <i>t</i> ₃)	0.148 (0.102)	0.0146 (0.0370)
(Exposure) _d × 1(<i>t</i> = <i>t</i> ₄)	0.0252 (0.141)	-0.0187 (0.0588)
Household f.e.	✓	✓
Survey-time f.e.	✓	✓
District Controls × Survey-time f.e.	✓	✓
Household controls × Survey-time f.e.	✓	✓
Observations	564,690	564,690
R-squared	0.707	0.706

Notes: The table shows the difference-in-differences estimate for consumption responses for each event-time after the demonetization shock relative to the pre-period (four event-time). The specification estimated is equation 17. The treatment variable is our measure of Exposure_d for the district (Column (1)) and takes the values of 1 if the measure of Exposure_d is in the top quartile of the distribution (Column (2)). The dependent variable log(*y*_{*h,d,t*}) is the log of total consumption as defined in Section 6. District-level controls include (log) pre-shock banking deposits, share of villages with ATM facilities, share of villages with a banking facility, share of rural population and level of population in the district. Household-level controls include pre-shock income, and age of head of the household. Standard errors are clustered at the district level. *** : *p* < 0.01, ** : *p* < 0.05, * : *p* < 0.1.

Parameter		Estimate	Standard error
<i>S</i>	Size of aggregate shock	0.246	(0.047)
<i>C</i>	Adoption complementarities	0.063	(0.004)
<i>k</i>	Speed of technology adjustment	0.163	(0.041)
<i>σ</i>	Volatility of idiosyncratic innovations	0.039	(0.011)
<i>M^e</i>	Returns to electronic payments when <i>X</i> _{<i>d,t</i>} = 0	0.970	(0.004)

Table 7: Point estimates and standard deviations for $\hat{\Theta}$. The parameters are estimated on a balanced panel with 512 districts and 8 months. The estimation procedure uses the simulated method of moments and is described in section 5. Standard errors are reported in parenthesis; they are computed using the bootstrap described in Appendix C.

Moment		Emp. value	Sim. value	Std. error	p-value
$\hat{\beta}$	Short-run average effect	0.030	0.032	0.004	0.32
$\hat{\gamma}$	Medium-run average effect	0.038	0.035	0.003	0.06
$\hat{\delta}$	Short-run effect of initial adoption	0.081	0.080	0.005	0.40
$\hat{\zeta}$	Medium-run effect of initial adoption	0.027	0.007	0.004	0.00
$\hat{\xi}$	Mean squared residuals	0.083	0.093	0.004	0.02
$\hat{\eta}$	Short-run between-district variance	0.098	0.096	0.004	0.26
$\hat{\kappa}$	Medium-run between-district variance	0.102	0.092	0.007	0.08
$\hat{\xi}$	Within-district variance	0.045	0.050	0.003	0.00
OID statistic	Degrees of freedom	p-value			
4.7076	3	0.1945			

Table 8: Model fit for the SMM estimation. The second column shows the empirical values of the moments used in the estimation of the model, and described in section 5. The simulated values are computed using the point estimates reported in table 7. We simulate 2000 panels consisting of 512 districts, and sample data from each panel at the monthly frequency. We then use each panel to compute the moments described in equation (13) and (14) and used in the estimation of the model. The standard error reported is the simulated sample standard error. The p-values reported for each moment are one-sided: they are the fraction of observations for which the simulated moment is at least as far from the average simulated moment as the empirical moment is. In the estimation procedure, we use the square root of all second order moments; the table above reports these standard deviations and not the variance. More details on the estimation procedure are reported in Appendix C.

	Baseline	Alternative policy interventions			
		$g = 0$	$g = 0.10$	$g = 0.25$	$g = 0.5$
Shock size (p.p.)	24.56	21.00	18.31	16.81	14.22
Shock half-life (months)	0.82	1.05	1.29	1.37	1.55
$\mathbb{E}_{t_0} [\Delta_{t_0} X_{d,t_0+T}]$ (p.p.)	7.22	8.34	8.32	8.23	7.82
$sd_{t_0} [\Delta_{t_0} X_{d,t_0+T}]$ (p.p.)	26.42	36.66	34.64	28.67	24.81

Table 9: Alternative policy interventions. The column marked “Baseline” report the estimated shock size, the shock half-life, and the mean and standard deviation of long-run changes in average adoption rates; we use $T = 3$ years and $s = 100$ simulations to compute these moments. The other columns report these moments under alternative scenarios. For each value of g — the aversion to dispersion in the planner’s objective function — we compute the value of the shock size and persistence which maximizes the objective described in equation (16).

B Appendix to section 3

B.1 Derivations

B.1.1 Value functions

The value of a firm which is operating under technology $x_{i,t}$ in period t , *after* any potential technology revisions, but before the realization of the money shock M_t , is:

$$V(x_{i,t}, M_{t-\Delta}, X_{t-\Delta}) = \mathbb{E}_{t-\Delta} \left[\Pi(x_{i,t}, M_t, X_t) \Delta + e^{-r\Delta} \left\{ (1 - e^{-k\Delta}) V_R(x_{i,t}, M_t, X_t) + e^{-k\Delta} V(x_{i,t}, M_t, X_t) \right\} \right].$$

Here, $V_R(x_{i,t}, M_t, X_{t-\Delta})$ denotes the value of a firm that receives the option to revise its technological choice early on in period $t + \Delta$ (and has entered that period with technology choice $x_{i,t}$). This value is given by:

$$V_R(x_{i,t}, M_t) = \begin{cases} V(e, M_t, X_t) - \kappa & \text{if } x_{i,t} = c \text{ and } V(e, M_t, X_t) - V(c, M_t, X_t) \geq \kappa \\ V(c, M_t, X_t) & \text{if } x_{i,t} = c \text{ and } V(e, M_t, X_t) - V(c, M_t, X_t) < \kappa \\ V(e, M_t, X_t) & \text{if } x_{i,t} = e \text{ and } V(e, M_t, X_t) - V(c, M_t, X_t) \geq 0 \\ V(c, M_t, X_t) & \text{if } x_{i,t} = e \text{ and } V(e, M_t, X_t) - V(c, M_t, X_t) < 0 \end{cases}$$

(Note that this assumes that κ is a fixed cost that does not scale with the size of the time period, Δ . So it should be interpreted in units of firms value.) Denote by:

$$B(M_{t-\Delta}, X_{t-\Delta}) = V(1, M_{t-\Delta}, X_{t-\Delta}) - V(0, M_{t-\Delta}, X_{t-\Delta}).$$

This is the value of a firm which has the electronics payment in place, relative to one that doesn't. Straight-forward computation then shows that the gross adoption benefits follow (3).

B.1.2 The relative value of adoption in complementarities model ($C > 0$ and $\kappa = 0$)

The conditional distribution of $M_{t+\Delta n}$, $n \geq -1$, given initial conditions $M_{t-\Delta}$ is:

$$M_{t+\Delta n} | M_{t-\Delta} \sim N \left((1 - e^{-(n+1)\theta\Delta}) M^c + e^{-(n+1)\theta\Delta} M_{t-\Delta}, \frac{1 - e^{-(n+1)\theta\Delta}}{1 - e^{-\theta\Delta}} \Delta \sigma^2 \right).$$

The net benefits of adoption can be written as:

$$B(M_{t-\Delta}, X_{t-\Delta}) = \mathbb{E}_{t-\Delta} \left[\sum_{n \geq 0} e^{-(r+k)\Delta n} (M^e + C X_{t+\Delta n} - M_{t+\Delta n}) \Delta \right]$$

We need to compute:

$$\begin{aligned} PV M_{t-\Delta} &= \mathbb{E}_{t-\Delta} \left[\sum_{n \geq 0} e^{-(r+k)\Delta n} M_{t+\Delta n} \Delta \right] = \sum_{n \geq 0} e^{-(r+k)\Delta n} \left\{ (1 - e^{-(n+1)\theta\Delta}) M^c + e^{-(n+1)\theta\Delta} M_{t-\Delta} \right\} \Delta \\ &= \sum_{n \geq 0} e^{-(r+k)\Delta n} \left\{ (1 - e^{-(n+1)\theta\Delta}) M_c + e^{-(n+1)\theta\Delta} M_{t-\Delta} \right\} \Delta \\ &= \frac{\Delta}{1 - e^{-(r+k)\Delta}} M^c + \frac{e^{-\theta\Delta} \Delta}{1 - e^{-(r+k+\theta)\Delta}} (M_{t-\Delta} - M^c) \end{aligned}$$

Finally, we need to compute:

$$PVX_{t-\Delta} = \mathbb{E}_{t-\Delta} \left[\sum_{n \geq 0} e^{-(r+k)\Delta n} X_{t+\Delta n} \Delta \right]$$

The dynamics of the adopter share are:

$$\begin{aligned} X_{t+\Delta n} &= (1 - e^{-k\Delta}) a_{e,t+\Delta n} + e^{-k\Delta} X_{t+\Delta(n-1)} \\ &= (1 - e^{-k\Delta}) a_{e,t+\Delta n} + e^{-k\Delta} (1 - e^{-k\Delta}) a_{e,t+\Delta(n-1)} + e^{-2k\Delta} X_{t+\Delta(n-2)} \\ X_{t+\Delta n} &= (1 - e^{-k\Delta}) \sum_{p=0}^n e^{-k\Delta(n-p)} a_{e,t+\Delta p} + e^{-k\Delta(n+1)} X_{t-\Delta} \end{aligned}$$

Thus we have:

$$\begin{aligned} PVX_{t-\Delta} &= \mathbb{E}_{t-\Delta} \left[\sum_{n=0}^{+\infty} e^{-(r+k)\Delta n} X_{t+\Delta n} \Delta \right] \\ &= \mathbb{E}_{t-\Delta} \left[\sum_{n=0}^{+\infty} e^{-(r+k)\Delta n} \left\{ (1 - e^{-k\Delta}) \sum_{p=0}^n e^{-k\Delta(n-p)} a_{t+\Delta p} + e^{-k\Delta(n+1)} X_{t-\Delta} \right\} \Delta \right] \\ &= (1 - e^{-k\Delta}) \mathbb{E}_{t-\Delta} \left[\sum_{n=0}^{+\infty} e^{-(r+k)\Delta n} \left\{ \sum_{p=0}^n e^{-k\Delta(n-p)} a_{t+\Delta p} \right\} \Delta \right] + \frac{e^{-k\Delta}}{1 - e^{-(r+2k)\Delta}} X_{t-\Delta} \Delta \end{aligned}$$

Moreover,

$$\begin{aligned} &\mathbb{E}_{t-\Delta} \left[\sum_{n=0}^{+\infty} e^{-(r+k)\Delta n} \left\{ \sum_{p=0}^n e^{-k\Delta(n-p)} a_{t+\Delta p} \right\} \right] \\ &= \mathbb{E}_{t-\Delta} \left[\sum_{n=0}^{+\infty} e^{-(r+2k)\Delta n} \left\{ \sum_{p=0}^n e^{k\Delta p} a_{t+\Delta p} \right\} \right] \\ &= \mathbb{E}_{t-\Delta} \left[\sum_{p=0}^{+\infty} e^{k\Delta p} a_{t+\Delta p} \left\{ \sum_{n=p}^{+\infty} e^{-(r+2k)\Delta n} \right\} \right] \\ &= \frac{1}{1 - e^{-(r+2k)\Delta}} \mathbb{E}_{t-\Delta} \left[\sum_{p=0}^{+\infty} e^{-(r+k)\Delta p} a_{t+\Delta p} \right] \\ &= \frac{1}{1 - e^{-(r+2k)\Delta}} \mathbb{E}_{t-\Delta} \left[\sum_{n=0}^{+\infty} e^{-(r+k)\Delta n} a_{t+\Delta n} \right] \end{aligned}$$

So:

$$\begin{aligned} PVX_{t-\Delta} &= \frac{1 - e^{-k\Delta}}{1 - e^{-(r+2k)\Delta}} \sum_{n=0}^{+\infty} e^{-(r+k)\Delta n} \mathbb{E}_{t-\Delta} [a_{t+\Delta n} \Delta] + \frac{\Delta e^{-k\Delta}}{1 - e^{-(r+2k)\Delta}} X_{t-\Delta} \\ &= \frac{1 - e^{-k\Delta}}{1 - e^{-(r+2k)\Delta}} PV A_{t-\Delta} + \frac{\Delta e^{-k\Delta}}{1 - e^{-(r+2k)\Delta}} X_{t-\Delta}, \end{aligned} \tag{18}$$

where:

$$PVA_{t-\Delta} = \sum_{n=0}^{+\infty} e^{-(r+k)\Delta n} \mathbb{E}_{t-\Delta} [a_{t+\Delta n} \Delta]. \quad (19)$$

Therefore,

$$\begin{aligned} B_{t-\Delta} &= \frac{\Delta}{1 - e^{-(r+k)\Delta}} (M^e - M^c) + \frac{\Delta e^{-\theta\Delta}}{1 - e^{-(r+k+\theta)\Delta}} (M^c - M_{t-\Delta}) \\ &\quad + \left\{ \frac{\Delta e^{-k\Delta}}{1 - e^{-(r+2k)\Delta}} X_{t-\Delta} + \frac{1 - e^{-k\Delta}}{1 - e^{-(r+2k)\Delta}} PVA_{t-\Delta} \right\} \times C. \end{aligned}$$

This shows, in particular, that the value of adoption depends positively on the current level of adopters, so long as $k < +\infty$. This is the reason for the positive slope in the adoption frontier $\Phi(\cdot)$.

B.2 Numerical solution method

In what follows we describe the numerical method for constructing the function $\Phi(\cdot)$ that characterizes equilibrium adoption strategies in the model with complementarities.

First, given a mapping $\Phi(\cdot) : [0, 1] \rightarrow \mathbb{R}$, define the functions:

$$\begin{aligned} PVA(M_{t-\Delta}, X_{t-\Delta}; \Phi) &= \sum_{n=0}^{+\infty} e^{-(r+k)\Delta n} \mathbb{E}_{t-\Delta} [\mathbf{1} \{M_{t+\Delta(n-1)} \geq \Phi(X_{t+\Delta(n-1)})\} \Delta] \\ B(M_{t-\Delta}, X_{t-\Delta}; \Phi) &= \frac{\Delta}{1 - e^{-(r+k)\Delta}} (M^e - M^c) + \frac{\Delta e^{-\theta\Delta}}{1 - e^{-(r+k+\theta)\Delta}} (M^c - M_{t-\Delta}) \\ &\quad + \left\{ \frac{\Delta e^{-k\Delta}}{1 - e^{-(r+2k)\Delta}} X_{t-\Delta} + \frac{1 - e^{-k\Delta}}{1 - e^{-(r+2k)\Delta}} PVA(M_{t-\Delta}, X_{t-\Delta}; \Phi) \right\} \times C. \end{aligned}$$

In the definition of the function $PVA(M_{t-\Delta}, X_{t-\Delta}; \Phi)$, the sequence $X_{t+\Delta(n-1)}$, in particular, is assumed to follow:

$$X_{t+\Delta n} = e^{-k\Delta} X_{t+\Delta(n-1)} + (1 - e^{-k\Delta}) \mathbf{1} \{M_{t+\Delta(n-1)} \geq \Phi(X_{t+\Delta(n-1)})\},$$

starting from $(X_{t-\Delta}, M_{t-\Delta})$.

With these definitions, the algorithm proceeds as follows:

- **Initialization:** We derive a threshold rule $\underline{\Phi}(\cdot)$ such that adoption of electronic money ($a_{e,t} = 1$) is a strictly dominant strategy, if and only if, $M_{t-\Delta} \leq \underline{\Phi}(X_{t-\Delta})$. For adoption of electronic money to be a strictly dominant strategy it must be that $B_{t-\Delta} \geq 0$ even if the firm expects no adoption at all by other firms, so that $PVA_{t-\Delta} = 0$. In that case:

$$B_{t-\Delta} = \frac{\Delta}{1 - e^{-(r+k)\Delta}} (M^e - M^c) + \frac{\Delta e^{-\theta\Delta}}{1 - e^{-(r+k+\theta)\Delta}} (M^c - M_{t-\Delta}) + \left\{ \frac{\Delta e^{-k\Delta}}{1 - e^{-(r+2k)\Delta}} X_{t-\Delta} \right\} \times C,$$

and so $B_{t-\Delta} \geq 0$, if and only if:

$$\begin{aligned} 0 &\leq M^e - M^c + \frac{e^{-\theta\Delta}(1 - e^{-(r+k)\Delta})}{1 - e^{-(r+k+\theta)\Delta}} (M^c - M_{t-\Delta}) + \left\{ \frac{e^{-k\Delta}(1 - e^{-(r+k)\Delta})}{1 - e^{-(r+2k)\Delta}} X_{t-\Delta} \right\} \times C \\ M_{t-\Delta} &\leq \underline{\Phi}(X_{t-\Delta}) = M^c - \frac{1 - e^{-(r+k+\theta)\Delta}}{e^{-\theta\Delta} - e^{-(r+k+\theta)\Delta}} (M^c - M^e) + \frac{e^{-k\Delta} - e^{-(r+2k+\theta)\Delta}}{e^{-\theta\Delta} - e^{-(r+2k+\theta)\Delta}} C X_{t-\Delta} \end{aligned}$$

Following similar steps, the upper threshold for $M_{t-\Delta}$ above which adoption of cash is a strictly dominant strategy is:

$$M_{t-\Delta} \geq \overline{\Phi}(X_{t-\Delta}) = \underline{\Phi}(X_{t-\Delta}) + \frac{e^{-k\Delta} - e^{-(r+2k+\theta)\Delta}}{e^{-\theta\Delta} - e^{-(r+2k+\theta)\Delta}} \frac{1 - e^{-k\Delta}}{e^{-k\Delta} - e^{-(r+2k)\Delta}} C.$$

Given these functions, we set $\underline{\Phi}^{(0)} = \underline{\Phi}$ and $\overline{\Phi}^{(0)} = \overline{\Phi}$.

- **Iteration:** At step n , given two functions $\underline{\Phi}^{(n)}$ and $\overline{\Phi}^{(n)}$, we compute their iterates as the solutions to:

$$B(\overline{\Phi}^{(n+1)}(X_{t-\Delta}), X_{t-\Delta}; \overline{\Phi}^{(n)}) = 0,$$

$$B(\underline{\Phi}^{(n+1)}(X_{t-\Delta}), X_{t-\Delta}; \underline{\Phi}^{(n)}) = 0.$$

These iterates are constructed on a linear grid for X .

- **Convergence:** We repeat the iteration step until $\max \left| \overline{\Phi}^{(n+1)}(.) - \overline{\Phi}^{(n)}(.) \right|$, $\max \left| \underline{\Phi}^{(n+1)}(.) - \underline{\Phi}^{(n)}(.) \right|$, and $\max \left| \overline{\Phi}^{(n+1)}(.) - \underline{\Phi}^{(n+1)}(.) \right|$ are below some threshold.

The only difficulties are in the computation of $PVA(M_{t-\Delta}, X_{t-\Delta}; \Phi)$, which in general has no closed form. To compute it, we use a Monte-Carlo approach: we simulate a large number of sample paths for the money stock starting at $M_{t-\Delta}$, and the implied path for $X_{t-\Delta}$ under the adoption rule $\Phi(.)$, and we then average across these sample paths. The threshold rule is interpolated linearly between the points of the grid for X .

B.3 The cash crunch in the frictionless model ($C = 0$ and $\kappa = 0$)

The left panel of figure D.1 reports the joint dynamics of (X_t, M_t) in the frictionless model. This graph is constructed under the assumption that $M^c > M^e$, so that on average, there are higher flow profits to technology c . The red line shows the average trajectory of a district which starts from point A , where $X_{-\Delta} = 0$ and $M_{-\Delta} = M^c$. At time 0, the shock shifts the economy from point A to point B . At point B , the stock of cash has fallen enough that the optimal technology choice of revising firms is to switch from c to e . As a result the number of firms using technology e , X_t , increases for a period of time. At the same time, the money stock reverts toward its long-run mean, M^c . After a certain time, it reaches the level \underline{M} at which firms that revise their technology choice choose c over e .⁷³ In the long-run, the district will therefore converge back to point A .

The top row of figure D.2 further illustrates this point. This graph plots the average response of a large number of districts to a common shock S . (The corresponding average path of M_t across the D districts is reported in figure D.2.) On average across districts, the number of firms using technology e rises during the period when M_t is still substantially below its long-run mean, but thereafter rapidly returns to zero, since firms that revise their technology choice find it optimal to switch back to c once M_t is close enough to its long-run mean. Thus, the frictionless model cannot generate permanent increases in the number of firms using technology e out of a transitory shock to M_t . Consistent with this, the long-run response of districts is zero, and in particular, it is independent of their individual exposures, as reported on the left panel of figure D.3.

Additionally, the sequence of technology choices by firms in a district, following the shock, is independent of the initial fraction of firms already using technology e prior to the shock, $X_{-\Delta}$. The left panel of figure D.1 illustrates this, by also showing (in blue) the trajectory of a district starting from $X_{-\Delta} = 0.4 > 0$. In the long-run, this district also converges to zero adoption. For the same reasons as in the fixed cost model, the mechanical relationship between adoption level and adoption rate in the model then implies that the change in the number of users of e depends negatively on the initial number of users, as illustrated in the right panel of figure D.3.

⁷³In the absence of complementarities ($C = 0$) or fixed costs ($\kappa = 0$), it is straightforward to see (using equation 3) that the gross value of adoption, B_t , only depends on the level of cash, M_t . Therefore, the technology choice is entirely determined by the level of the aggregate shock, $M_{t-\Delta}$. One can then verify that, given the functional forms for flow profits, firms switch from c to e whenever $M_{t-\Delta} \leq \underline{M} = M^c - \frac{1 - e^{-(r+k+\theta)\Delta}}{e^{-\theta\Delta} - e^{-(r+k+\theta)\Delta}} (M^c - M^e)$. When shocks are purely transitory ($\theta = +\infty$), firms either always or never switch (depending on whether $M^e \geq M^c$), while when shocks are permanent ($\theta = 0$), firms switch as soon a shock pushes M_t below the flow profits from technology e in the absence of complementarities, M^e .

C Appendix to section 5

Let Y and Z denote the dependent and independent variables in the system of equations (13)-(14); we first construct the OLS estimate of the data moments, $\hat{\Xi} = (Z'Z)^{-1}Z'Y$. We then estimate the variance-covariance matrix of $\hat{\Xi}$ using the bootstrap. Specifically, we let:

$$var\left(\hat{\Xi}\right) = \frac{1}{B-1} \sum_{b=1}^B \left(\hat{\Xi}_b - \hat{\Xi}\right)' \left(\hat{\Xi}_b - \hat{\Xi}\right),$$

where $\hat{\Xi}_b$ is the estimate obtained in replication b of the bootstrap. We use $B = 100$ and sample with replacement district by district.

The point estimate for the $N_p \times 1$ vector of parameters Θ is obtained by solving:

$$\hat{\Theta} = \arg \min \left(\hat{\Xi} - \frac{1}{S} \sum_{s=1}^S \Xi_{sim}(\Theta; \gamma_s) \right)' W \left(\hat{\Xi} - \frac{1}{S} \sum_{s=1}^S \Xi_{sim}(\Theta; \gamma_s) \right).$$

In this objective, S is the number of simulations, and $\Xi_{sim}(\Theta; \gamma_s)$ is the same vector of moments as above, estimated using data produced by simulation s . We use $S = 20$ simulations, in keeping with the recommendations of Michaelides and Ng (2000). Each simulation has the same size as the panel data; data is sampled monthly from model simulations. We simulate data with a burn-in period of 10 years for each district. Additionally, γ_s is a vector of random disturbances for simulation s , which we keep constant across values of Θ for which the objective is evaluated. We use Matlab's patternsearch routine to minimize the objective, with 20 randomly drawn starting points for Θ .

Following the literature (Pakes and Pollard, 1989; Rust, 1994; Hennessy and Whited, 2005, 2007; Taylor, 2010), we use the optimal weighting matrix:

$$W = \frac{1}{N_m} var\left(\hat{\Xi}\right)^{-1}.$$

The variance-covariance matrix for $\hat{\Theta}$, the vector of estimated parameters, is obtained as:

$$\Omega = \left(1 + \frac{1}{S}\right) \left\{ \left(\frac{\partial G}{\partial \Theta}(\hat{\Theta}) \right)' W \left(\frac{\partial G}{\partial \Theta}(\hat{\Theta}) \right) \right\}^{-1},$$

with:

$$G(\Theta) \equiv \hat{\Xi} - \frac{1}{S} \sum_{s=1}^S \Xi_{sim}(\Theta; \gamma_s).$$

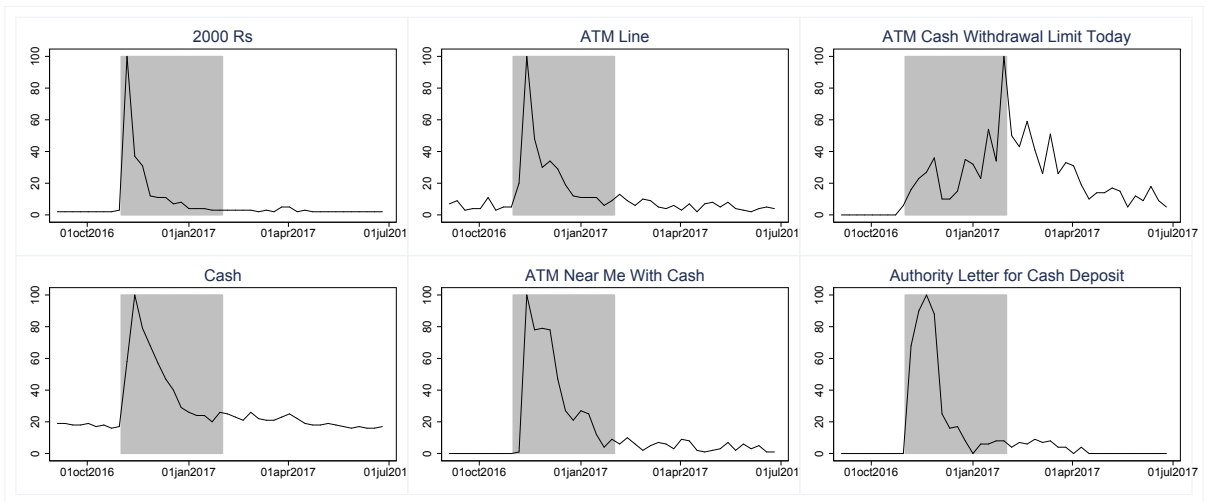
We approximate the Jacobian of $G(\cdot)$ using numerical differentiation. We also report the following test statistic for over-identifying restrictions:

$$J = \frac{S}{1+S} G(\hat{\Theta})' \left(var\left(\hat{\Xi}\right)^{-1} \right) G(\hat{\Theta}),$$

which is distributed as a χ -squared with $N_m - N_p$ degrees of freedom under the null that the over-identifying restrictions hold. Additionally, we use $S_{CI} = 2000$ simulations of the panel, with parameters set to $\hat{\Theta}$, to construct the standard errors and p-values reported in table 8.

D Appendix figures and tables

Figure D.1: Evidence from Google Search Trends



Notes: The figure reports the daily plot between September 2016 and July 2017 of Google Searches for several key words that could be representative of public actions and information associated with the demonetization shocks. Data are obtained by Google Trends, and the index is normalized by Google to be 0 to 100, with a value of 100 assigned to the day with the maximum number of searches made for that topic. Source: Google Search Index.

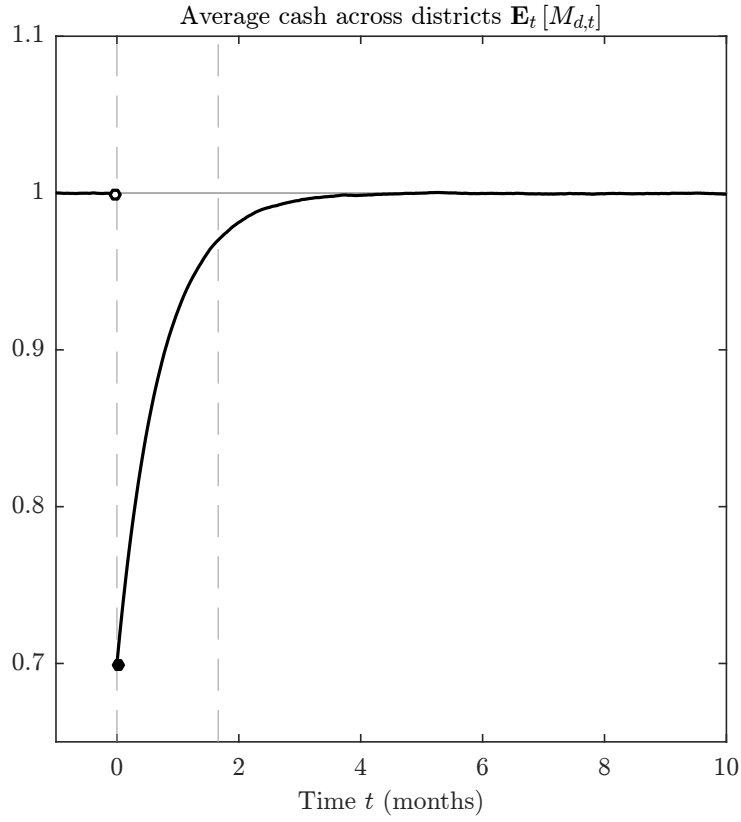


Figure D.2: Path of the average level of cash across districts, $\mathbb{E}_t[M_{d,t}]$, after the cash crunch. The first grey dashed line indicates the date of the shock, and the second one indicates the date at which M_t is back to within 90% of its long-run value, $M_t = M^c = 1$. The model is simulated for $D = 10^4$ districts, with a burn-in period of 5 years. The persistence of the shock is $\theta = 1.38$, corresponding to a half-life of two weeks.

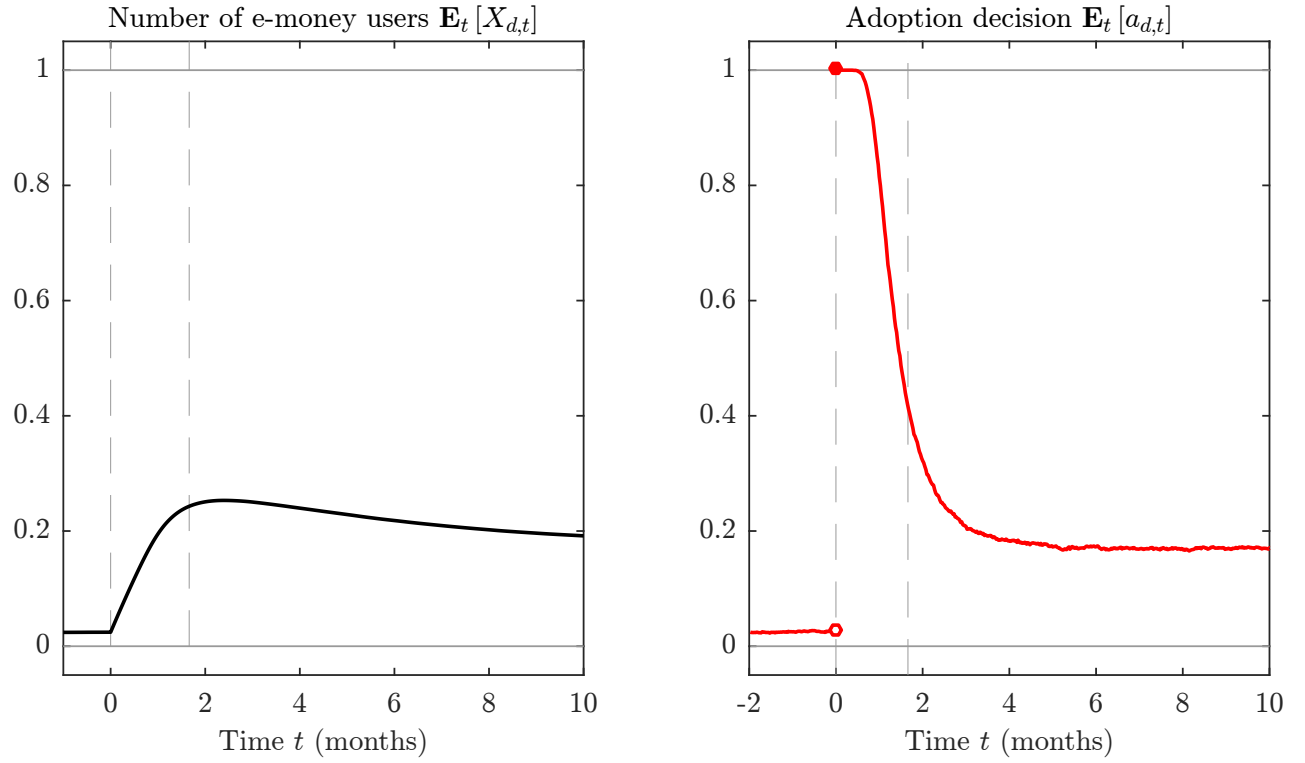


Figure D.3: Average number of users ($\mathbb{E}_t[X_{d,t}]$, left column) and average adoption decision ($\mathbb{E}_t[a_{d,t}]$, right column) after the cash crunch in the complementarities model ($C > 0$ and $\kappa = 0$). The results reported here are generated using a version of the model where $\theta > k$ (the shock is transitory relative to the adjustment speed of firms.) Specifically, the model is solved with $k = 0.2$, corresponding to an average waiting time between technology resets of 5.0 months, while the persistence of the shock is $\theta = 1.38$, corresponding to a half-life of two weeks.

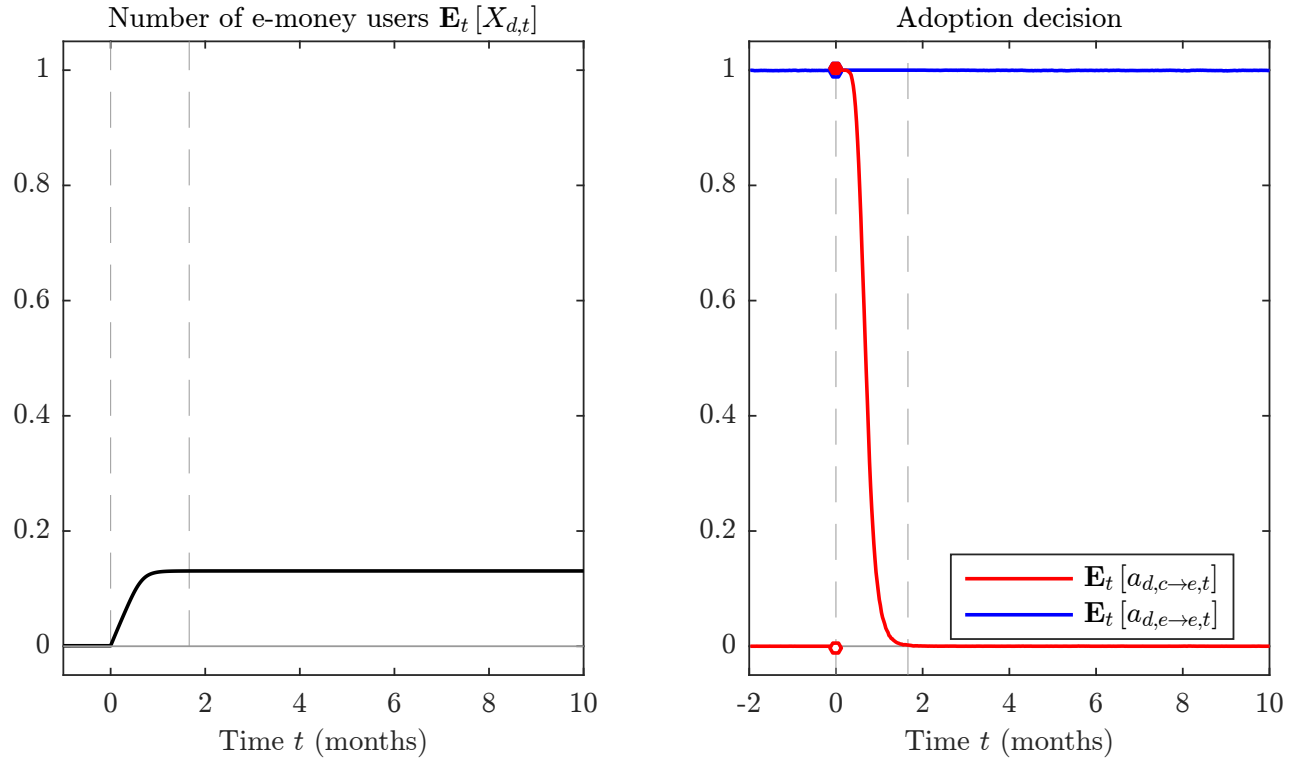


Figure D.4: Average number of users ($\mathbb{E}_t[X_{d,t}]$, left column) and average adoption decisions (right column) after the cash crunch in the fixed cost model ($C = 0$ and $\kappa > 0$). The graph on the right panel reports separately the adoption decision of firms currently using cash and the adoption decision of firms currently using electronic money. The calibration assumes that $M^e > M^c$ and $k = 0.2$, corresponding to an average waiting time between technology resets of 5.0 months.

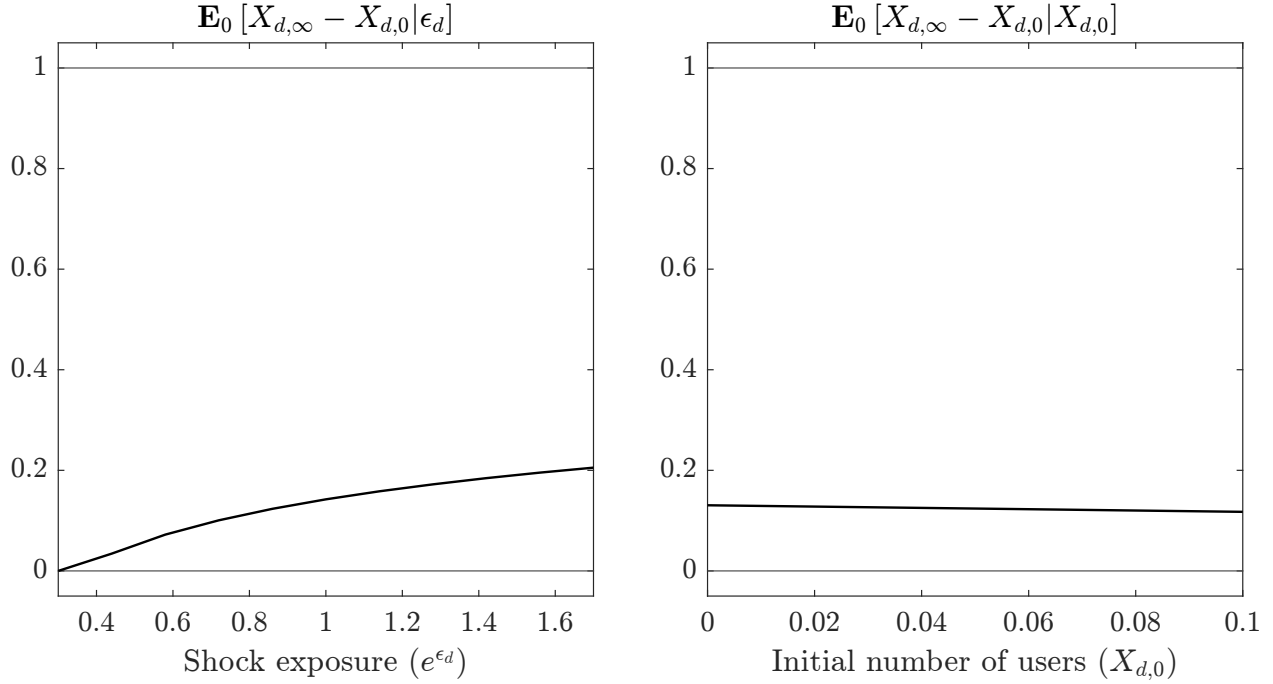


Figure D.5: Conditional impulse responses in the fixed cost model ($C > 0$ and $\kappa = 0$). These impulse responses are generated from the same type of simulations as in figure D.4. The left column reports the relationship between the district's exposure to the shock, proxied by e^{ϵ_d} (with a value of 1 indicating an average exposure to the shock), and the long-run change in the number of users after the shock. The right column reports the relationship between the initial number of users, $X_{d,0}$, and the long-run change in the number of users after the shock. The long-run number of users in the left panel is defined as $E_0 [X_{d,\infty} - X_{d,0} | \epsilon_d] = \lim_{t \rightarrow +\infty} E_0 [X_{d,t} - X_{d,0} | \epsilon_d]$ (and similarly for the right panel). For both columns, in each district, the adoption path is constructed by averaging across 10^3 draws. The limit as $t \rightarrow \infty$ is obtained by simulating the response of each district for five years, and using the end-of-simulation values.

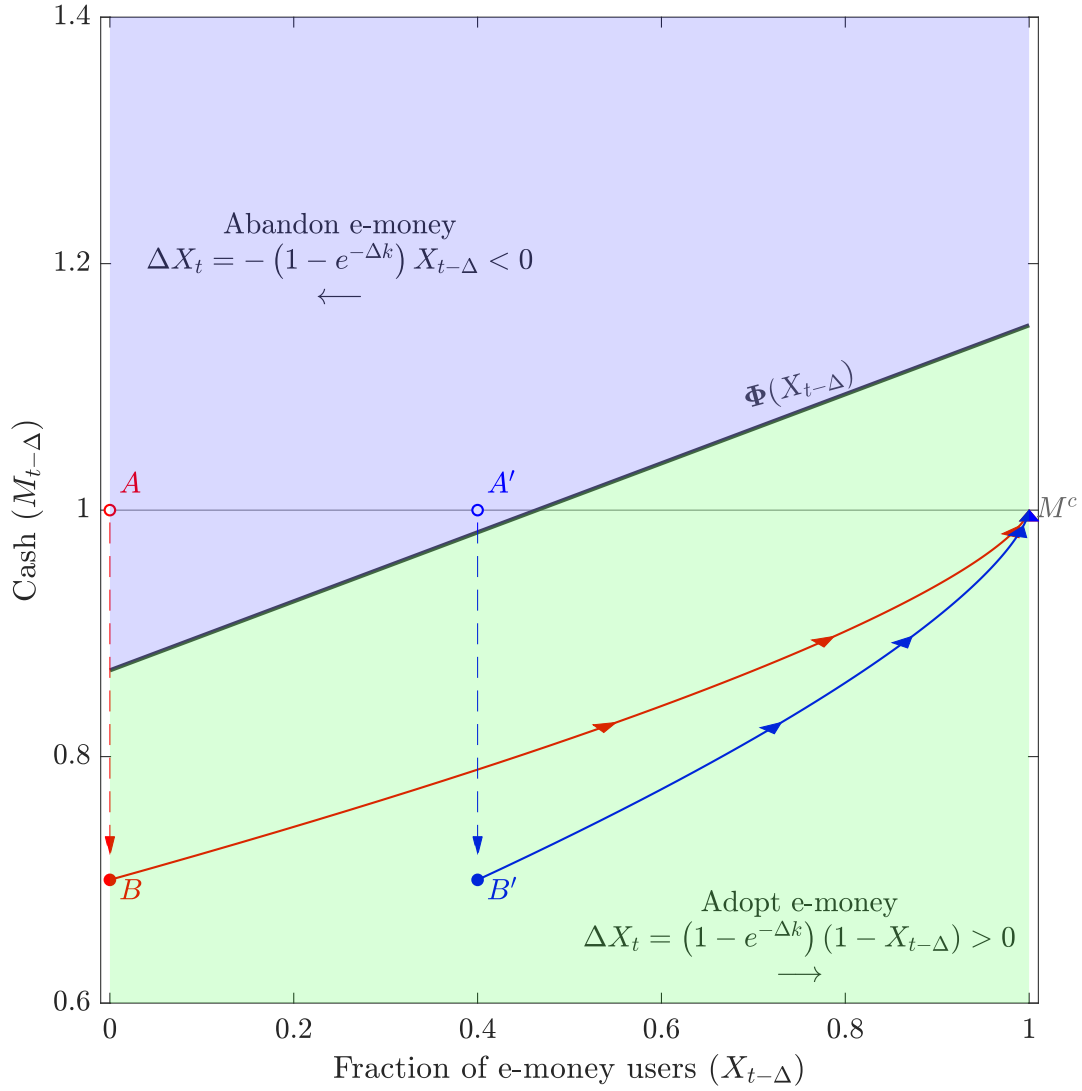


Figure D.6: Adoption dynamics in response to a large decline in M_t in the complementarities model ($C > 0$ and $\kappa = 0$). The model illustrated here corresponds to the case $\theta < k$ (the shock is transitory relative to the adjustment speed of firms.) The red line shows the path of a district that starts with a low adoption level $X_{d,0} = 0$. The blue line shows the path of a district that starts with a high adoption level, $X_{d,0} = 0.4$. The paths are constructed assuming that each district receives no other shock than the initial decline in M_t , i.e. that $\epsilon_t = 0$ for all $t > 0$.

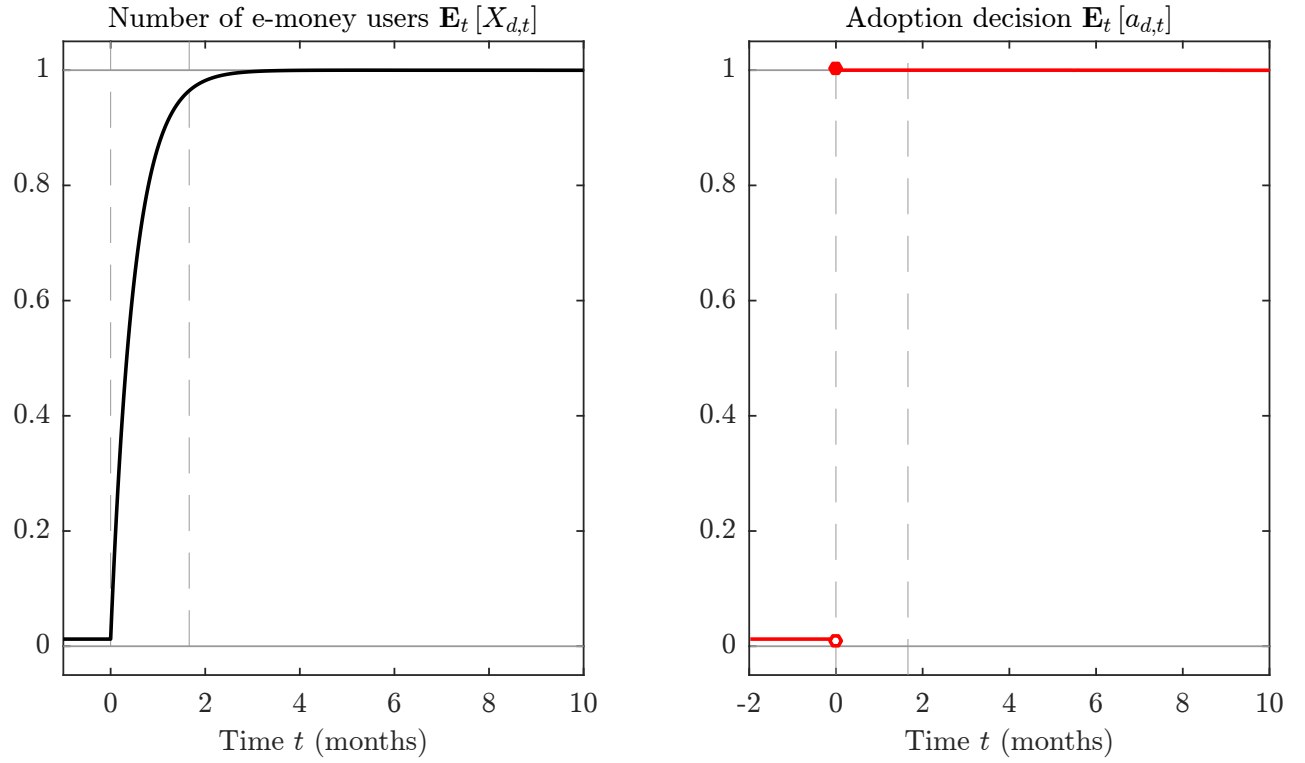


Figure D.7: Average number of users ($\mathbb{E}_t[X_{d,t}]$, left column) and average adoption decision ($\mathbb{E}_t[a_{d,t}]$, right column) after the cash crunch in the complementarities model ($C > 0$ and $\kappa = 0$). The results reported here are generated using a version of the model where $\theta < k$ (the shock is persistent relative to the adjustment speed of firms.) Specifically, the model is solved with $k = 2$, corresponding to an average waiting time between technology resets of 2 weeks, while the persistence of the shock is $\theta = 1.38$, corresponding to a half-life of two weeks.

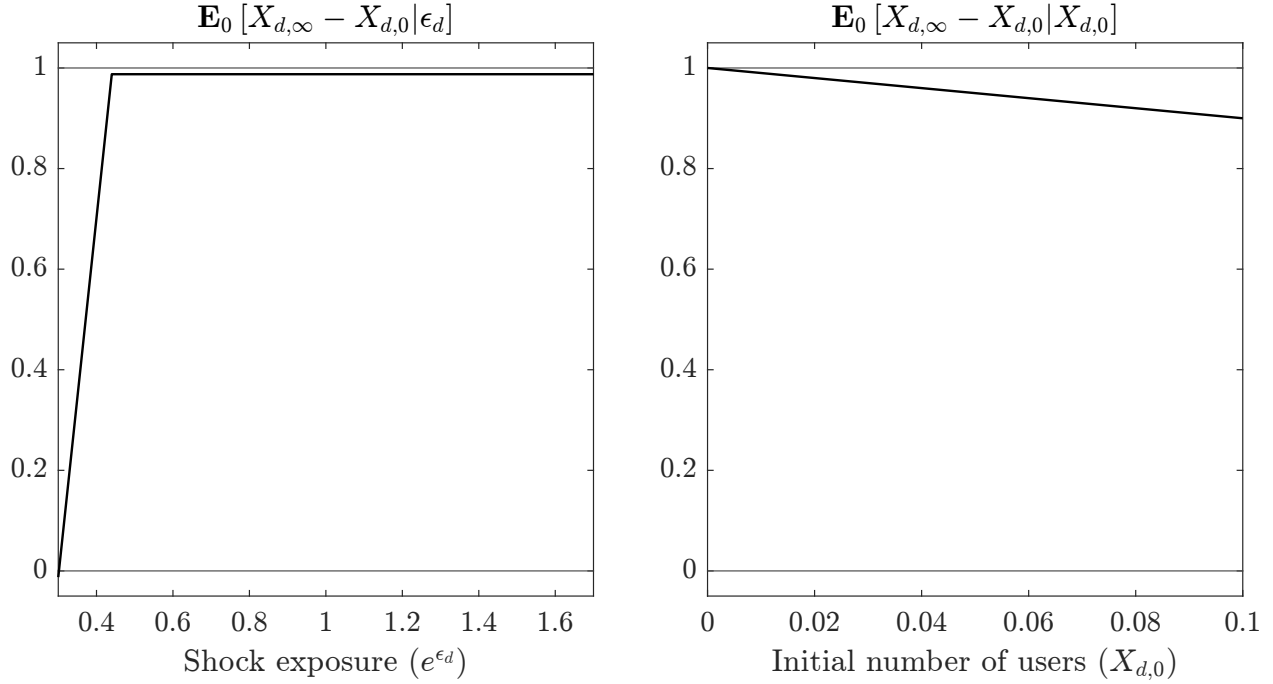
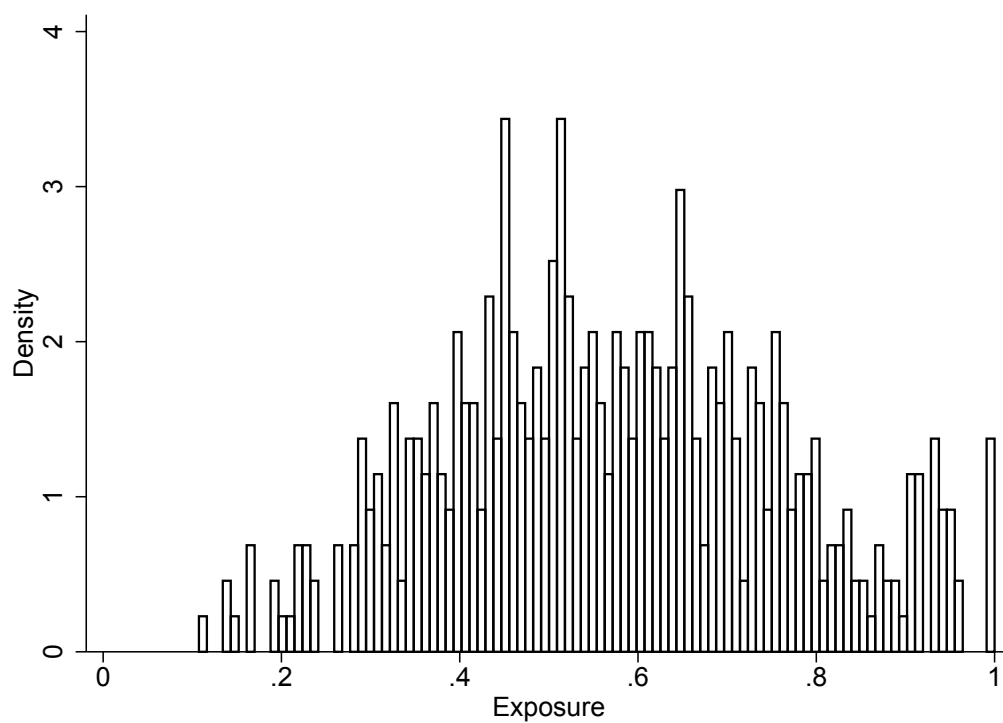


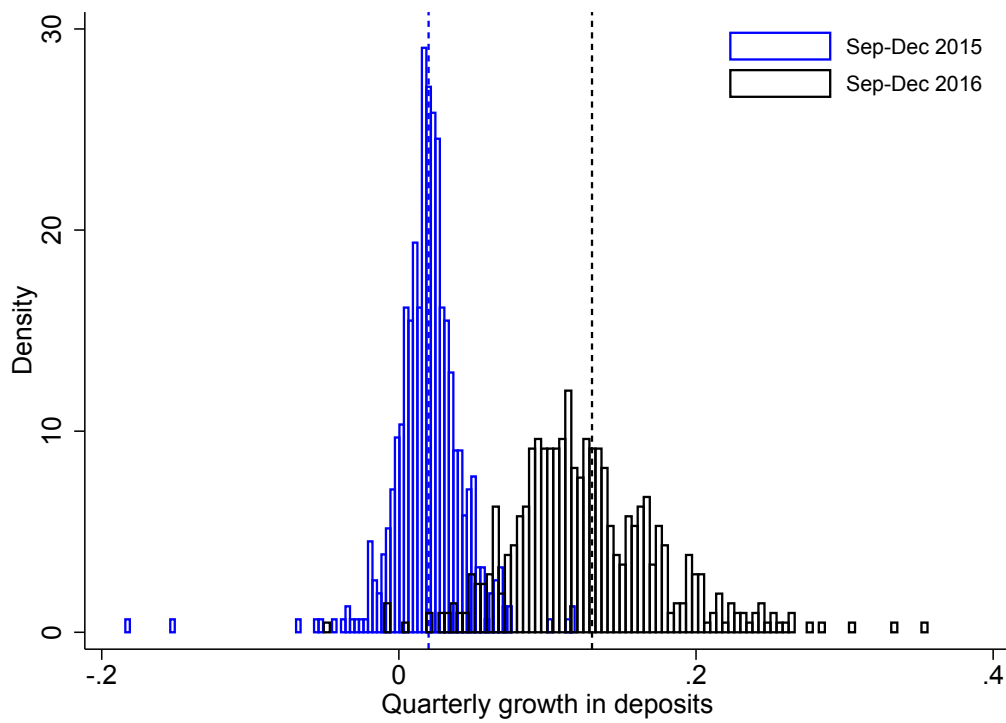
Figure D.8: Conditional impulse responses in the complementarities model ($C > 0$ and $\kappa = 0$). These impulse responses are generated from the same type of simulations as in figure D.7, that is, the case where $\theta < k$ (the shock is persistent relative to the adjustment speed of firms.) The left column reports the relationship between the district's exposure to the shock, proxied by e^{ϵ_d} (with a value of 1 indicating an average exposure to the shock), and the long-run change in the number of users after the shock. The right column reports the relationship between the initial number of users, $X_{d,0}$, and the long-run change in the number of users after the shock. The long-run number of users in the left panel is defined as $E_0 [X_{d,\infty} - X_{d,0} | \epsilon_d] = \lim_{t \rightarrow +\infty} E_0 [X_{d,t} - X_{d,0} | \epsilon_d]$ (and similarly for the right panel). For both columns, in each district, the adoption path is constructed by averaging across 10^3 draws. The limit as $t \rightarrow \infty$ is obtained by simulating the response of each district for five years and using the end-of-simulation values.

Figure D.9: Distribution of Exposure_d across districts



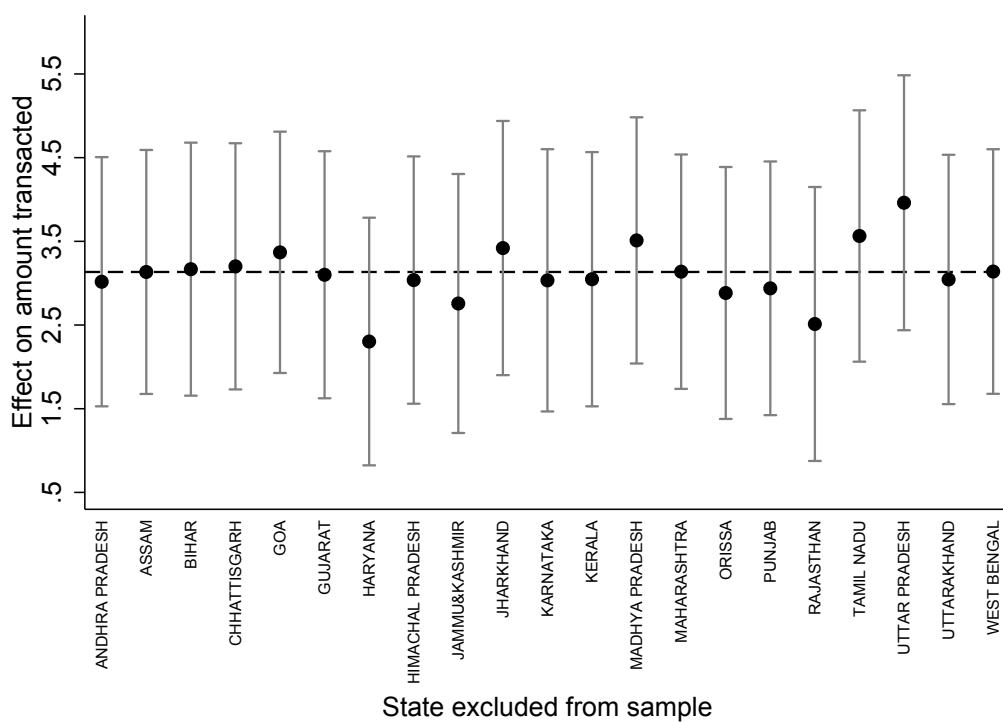
Notes: The figure shows the distribution of Exposure_d (as described in Section 2) across Indian districts. Source: Reserve Bank of India.

Figure D.10: Distribution of growth in deposits across districts



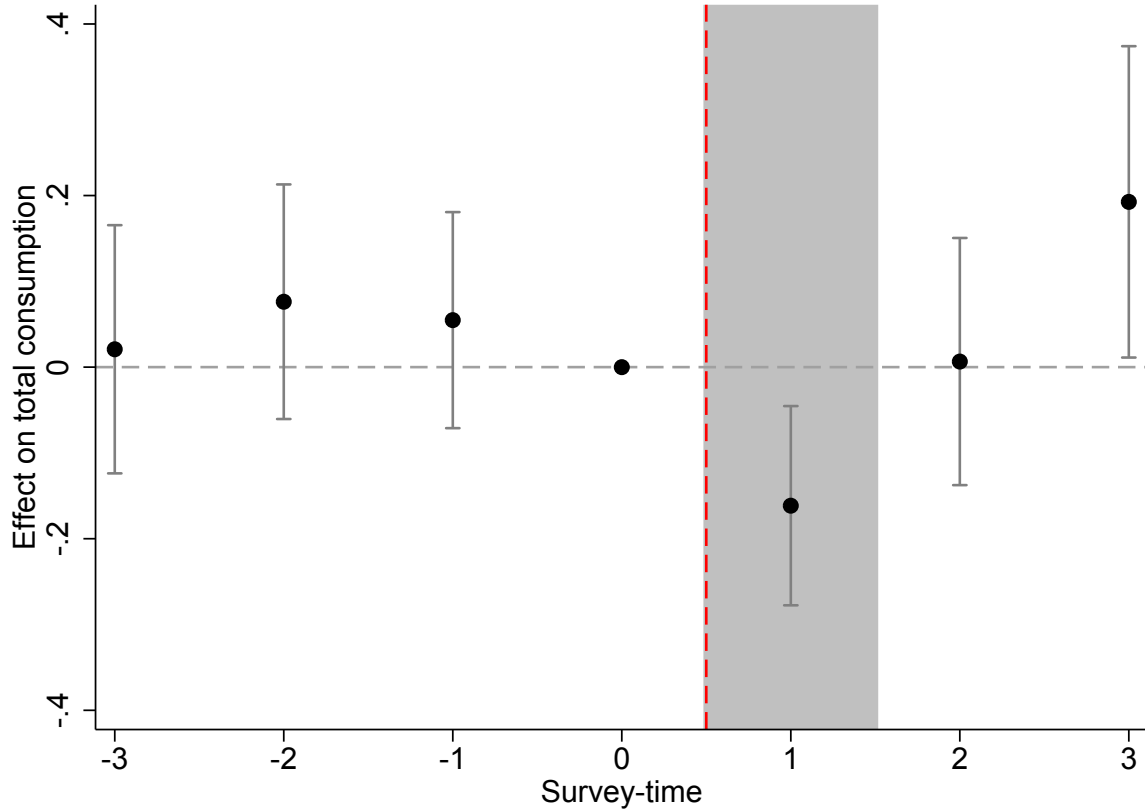
Notes: Distribution across deposits of the growth in total banking sector deposits from October to December during the year 2015 (blue) and 2016 (black). The vertical dashed lines represents the corresponding mean deposit growth for these years. Source: Reserve Bank of India.

Figure D.11: Robustness: one-state out



Notes: This figure reports the result from a robustness in which we exclude from the main analysis one state at the time and we recalculate the main coefficient of interest. For main analysis, we consider the specification in which we look at amount of transactions as an outcome and we consider the coefficient on post multiplied to the chest exposure measure. Each bar reports the main coefficient for the specification that excludes the state in the x-axis and the 95% confidence interval. The horizontal dashed line is the main coefficient from the main table of the paper, added for reference.

Figure D.12: Consumption responses based on exposure to the shock



Notes: The figure plots estimates of consumption responses depending on exposure to the shock ($Exposure_d$). The specification we estimate is a version of equation 17 in which each coefficient is based on the interaction of the treatment variable with a event-time dummy. We report the event-time estimates of the coefficient δ . The treatment is our measure of $Exposure_d$ as described in Section 2. The dependent variable on y -axis is the (log) total expense by household (as described in Section 4). 95% confidence intervals are represented with the vertical lines; standard errors are clustered at the district level. Source: CMIE Consumption Data.

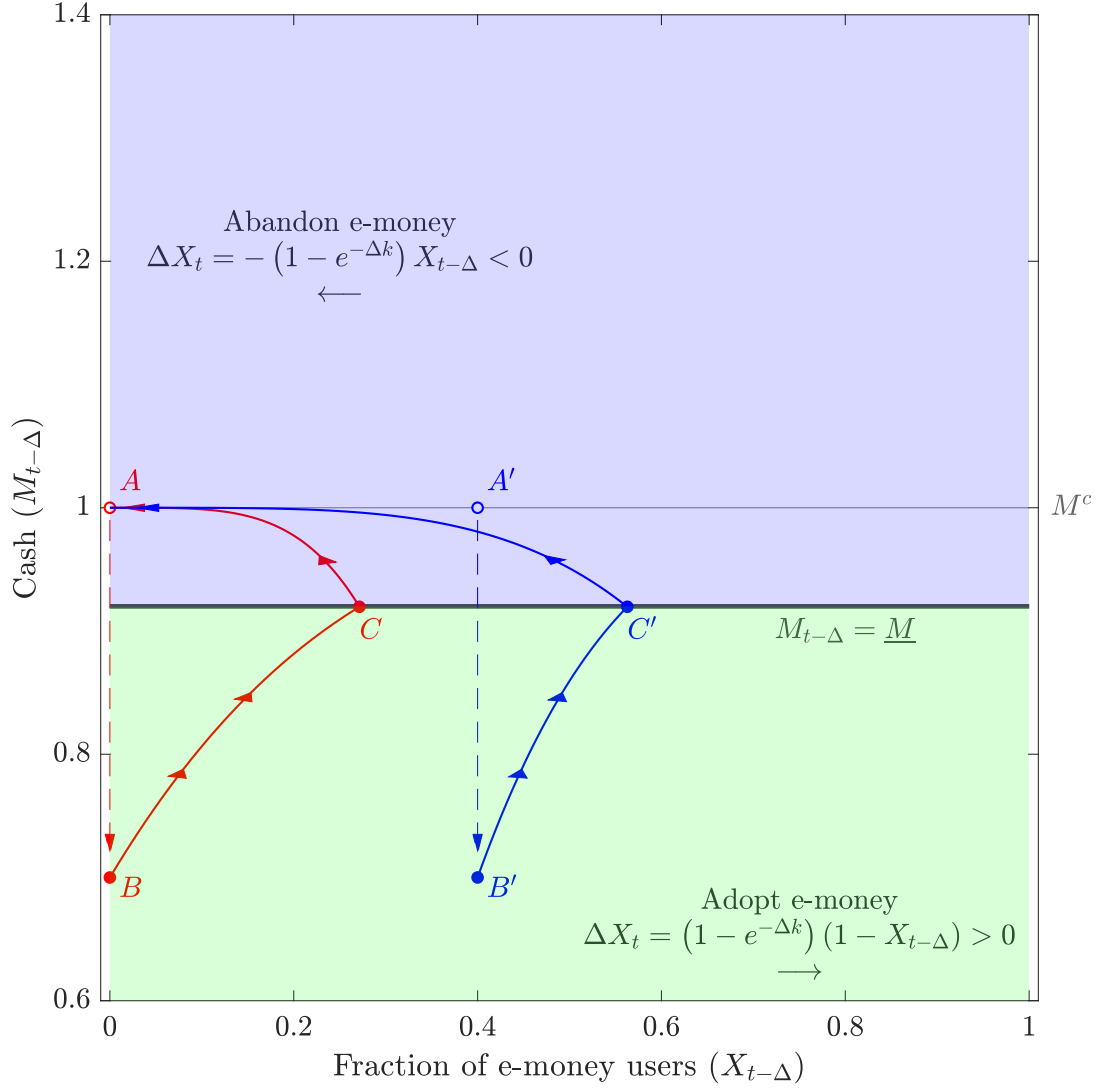


Figure D.1: Adoption dynamics in response to a large decline in M_t in the frictionless model ($C = 0$ and $\kappa = 0$). The red line shows the path of a district that starts with a low adoption level $X_{d,0} = 0$. The blue line shows the path of a district that starts with a high adoption level, $X_{d,0} = 0.4$. The paths are constructed assuming that each district receives no other shock than the initial decline in M_t , i.e. that $\epsilon_t = 0$ for all $t > 0$.

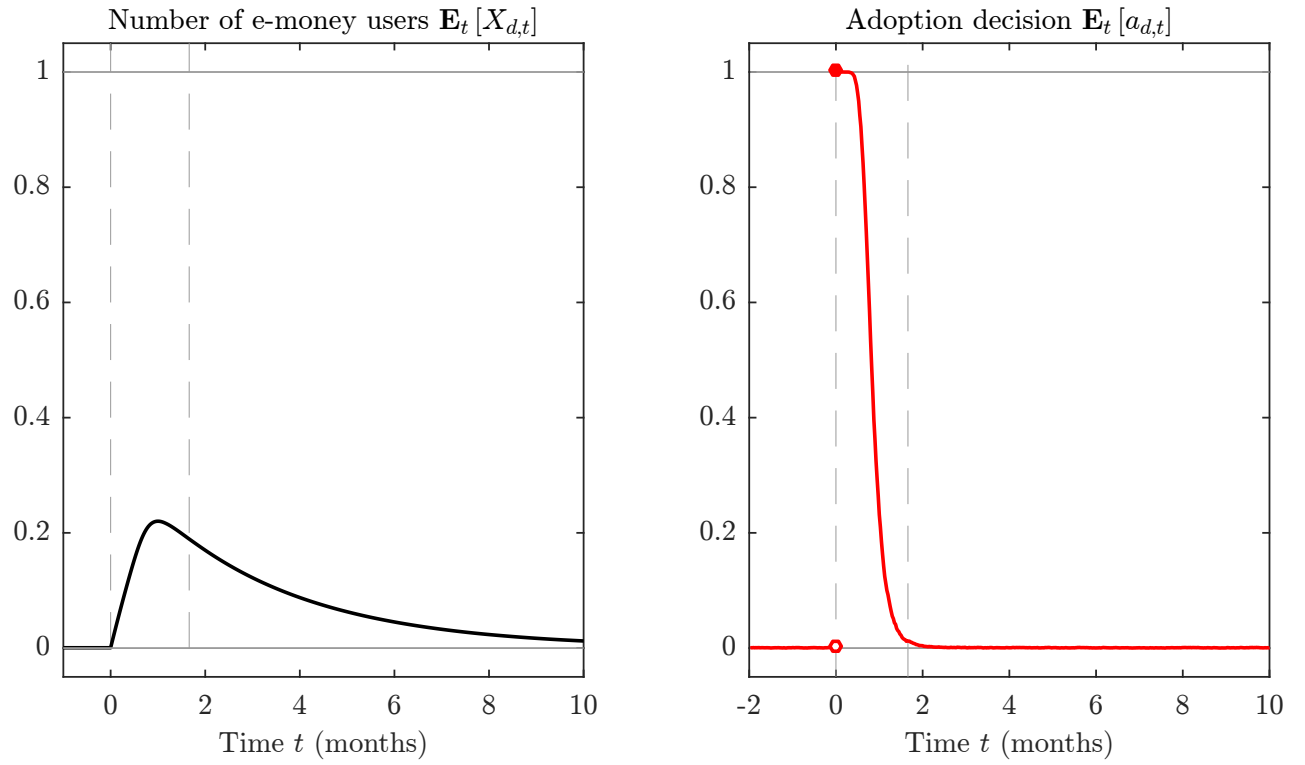


Figure D.2: Average number of users ($\mathbb{E}_t[X_{d,t}]$, left column) and average adoption decision ($\mathbb{E}_t[a_{d,t}]$, right column) after the cash crunch in the frictionless model ($C = 0$ and $\kappa = 0$).

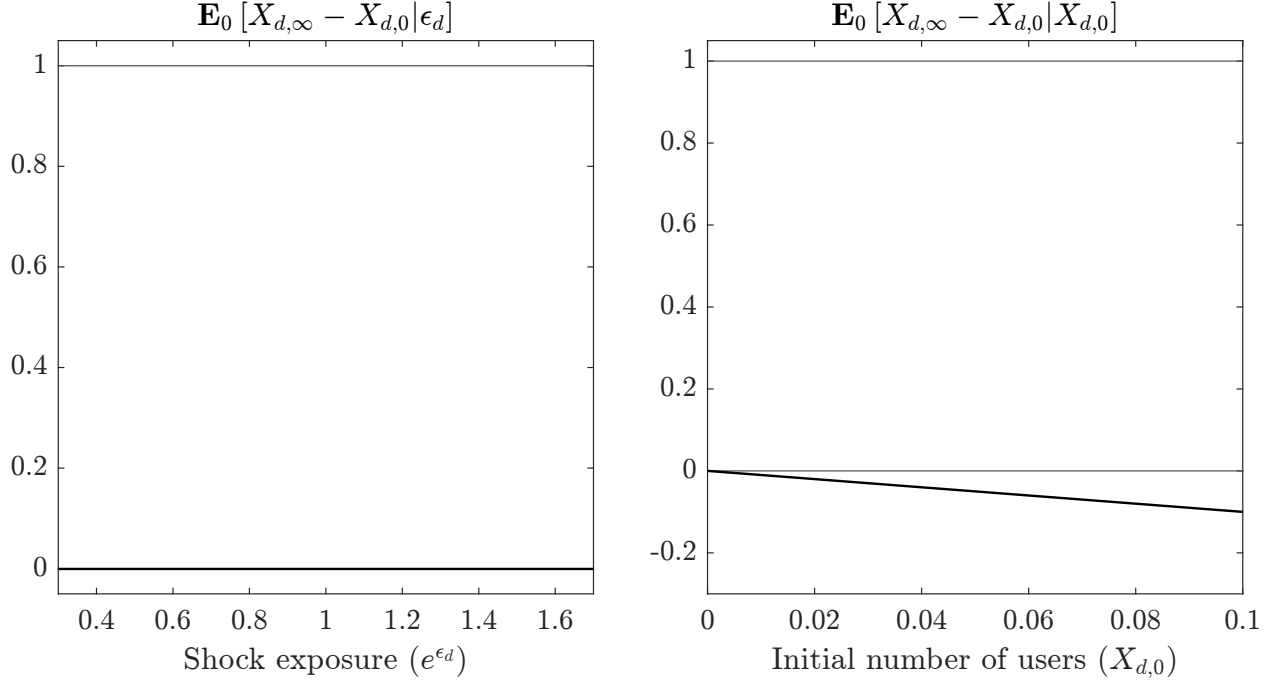
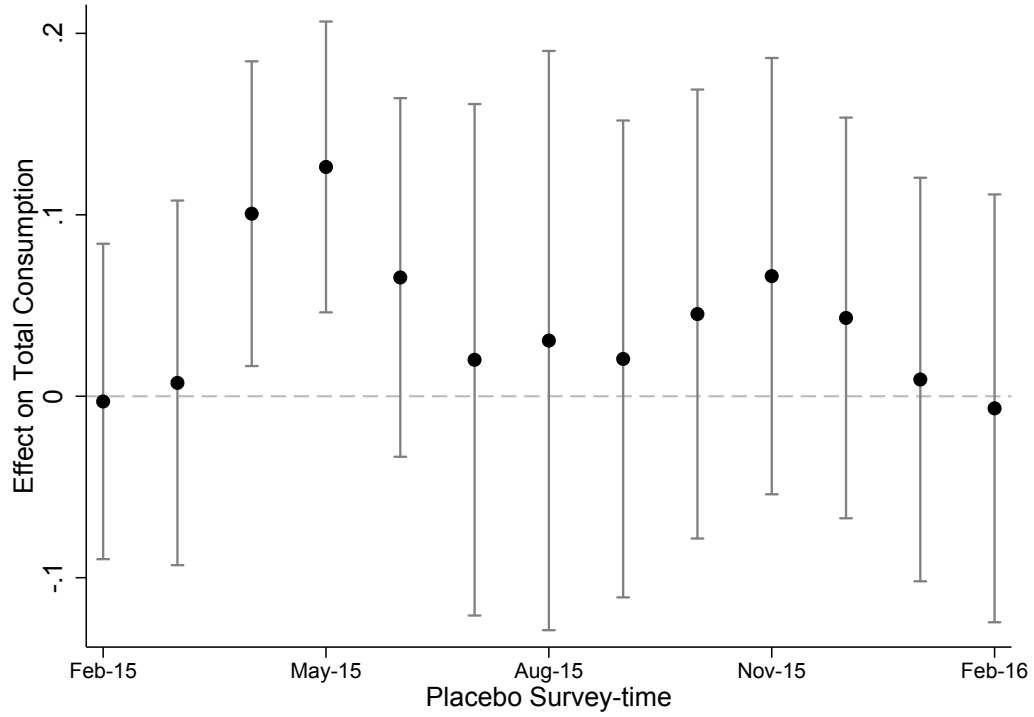


Figure D.3: Conditional impulse responses in the frictionless model ($C = 0$ and $\kappa = 0$). These impulse responses are generated from the same type of simulations as in figure D.7, that is, the case where $\theta < k$ (the shock is persistent relative to the adjustment speed of firms.) The left column reports the relationship between the district's exposure to the shock, proxied by e^{ϵ_d} (with a value of 1 indicating an average exposure to the shock), and the long-run change in the number of users after the shock. The right column reports the relationship between the initial number of users, $X_{d,0}$, and the long-run change in the number of users after the shock. The long-run number of users in the left panel is defined as $E_0 [X_{d,\infty} - X_{d,0} | \epsilon_d] = \lim_{t \rightarrow +\infty} E_0 [X_{d,t} - X_{d,0} | \epsilon_d]$ (and similarly for the right panel). In the left panel, the long-run change in the number of users is represented by the thick black line (which, for this version of the model, is constant and equal to 0). For both columns, in each district, the adoption path is constructed by averaging across 10^3 draws. The limit as $t \rightarrow \infty$ is obtained by simulating the response of each district for five years and using the end-of-simulation values.

Figure D.4: Consumption responses based on placebo shocks



Notes: The figure plots the estimates of consumption responses depending on exposure to the shock where we assume the occurrence of a “fake” shock in each survey-time corresponding to each entry on the x -axis. The specification we estimate is a version of equation 17 in which each coefficient is based on the interaction of the treatment variable (Exposure_d) with an event-time dummy. We report the coefficient δ for the event-time right after shock. The treatment variable is our measure of Exposure_d for the district (as described in Section 2). The dependent variable $\log(y_{h,d,t})$ is the log of total consumption (as described in Section 4). 95% confidence intervals are represented with the vertical lines; standard errors are clustered at the district level. Source: CMIE Consumption Data.

Table D.1: Share of Chest Banks and Deposit Growth

	$\Delta \log(\text{deposits})$		$\Delta \log(\text{deposits}^{adj.})$		$\Delta \log(\text{deposits}^N)$	
	(1)	(2)	(3)	(4)	(5)	(6)
Chest Exposure	0.094*** [0.013]	0.083*** [0.012]	0.085*** [0.013]	0.075*** [0.012]	1.821*** [0.257]	1.621*** [0.238]
log(Pre Deposits)		-0.035*** [0.003]		-0.035*** [0.003]		-0.677*** [0.063]
% villages with ATM		0.023 [0.040]		0.020 [0.042]		0.445 [0.769]
% villages with banks		-0.051** [0.023]		-0.051** [0.024]		-1.000** [0.449]
Rural Pop./Total Pop.		-0.063*** [0.016]		-0.070*** [0.017]		-1.224*** [0.317]
log(population)		0.036*** [0.003]		0.035*** [0.003]		0.707*** [0.068]
Observations	512	512	512	512	512	512
R-squared	0.118	0.313	0.099	0.290	0.118	0.313
District Controls		✓		✓		✓

Notes: The table reports the results from regression of the district-level deposit growth (between September 30, 2016 and December 31, 2016) on the measure of Exposure_d for the district (as described in Section 2). Columns (1) and (2) use the measure of change in total deposits. Columns (3) and (4) uses the measure of abnormal growth in total deposits, which adjust for the normal deposit growth by the growth in district-deposit in same quarter for the last two years. Column (5) and (6) uses the dependent variable of deposit growth that is normalized to have mean zero and standard deviation 1. Odd columns shows the correlation without any controls. Even columns include the district-level controls for (log) pre-shock banking deposits, share of villages with ATM facilities, share of villages with banking facility, share of rural population and level of population in the district. Robust standard errors are reported in parentheses; *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table D.2: Exposure_d and Deposit Growth (pre-shock quarters)

	(1) 201604	(2) 201603	(3) 201602	(4) 201601	(5) 201504	(6) 201503	(7) 201502	(8) 201501	(9) 201404	(10) 201403	(11) 201402	(12) 201401
Chest Exposure	1.621*** [0.238]	-0.404 [0.260]	0.476** [0.236]	0.137 [0.234]	0.163 [0.268]	0.342 [0.255]	-0.040 [0.231]	0.315 [0.240]	0.345 [0.291]	-0.734*** [0.280]	0.165 [0.257]	0.012 [0.269]
Observations	512	512	512	512	512	512	512	512	512	512	512	512
R-squared	0.313	0.027	0.026	0.162	0.020	0.054	0.044	0.061	0.017	0.037	0.100	0.124
District Controls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: Regression of district-level deposit growth for all eleven quarter before the shock (2016 Q4) on the density of chest banks in the district. The dependent variable is normalized to have mean zero and standard deviation 1. Treatment variable is our measure of Exposure_d for the district (as described in Section 2). District-level controls include (log) pre-shock banking deposits, share of villages with ATM facilities, share of villages with banking facility, share of rural population and level of population in the district. Standard error in parentheses; * * * : $p < 0.01$, * * : $p < 0.05$, * : $p < 0.1$.

Table D.3: Firms adoption rates in the simulated data

	No complementarities ($C = 0$)	Complementarities ($C > 0$)
ρ	0.862 (0.861,0.864)	0.863 (0.862,0.864)
β	-0.175 (-0.180,-0.170)	-0.177 (-0.183,-0.171)
γ	-0.016 (-0.020,-0.011)	0.198 (0.196,0.200)
Observations per simulation	2,100,000	2,100,000
Average R-sq.	0.754	0.837

Notes: This table reports the estimates of the panel data regression model 11 on simulated firm-level data. The coefficient ρ is the autocorrelation to a firm's technology choice, $x_{i,d,t}$, while the coefficient β captures the dependence on the stock of money, $M_{d,t-\Delta}$, and the coefficient γ captures the dependence on the existing share of adopters, $X_{d,t-\Delta}$. The simulated data are aggregated at the district level and sampled monthly; see text for details. The 95% confidence interval is reported in parentheses.

Table D.4: District adoption rates based on initial adoption in electronic payment data: OLS

	log(amount)		log(# users)		log(# switchers)	
	(1)	(2)	(3)	(4)	(5)	(6)
$\mathbf{1}(\text{Any Adopter})_d \times \mathbf{1}(t \geq t_0)$	1.416*** [0.379]		1.751*** [0.188]		1.312*** [0.150]	
$\log(\text{pre-amount})_d \times \mathbf{1}(t \geq t_0)$		0.050 [0.050]		0.173*** [0.022]		0.127*** [0.018]
Observations	6,846	6,846	6,846	6,846	6,552	6,552
R-squared	0.849	0.848	0.880	0.878	0.842	0.839
District f.e.	✓	✓	✓	✓	✓	✓
Month f.e.	✓	✓	✓	✓	✓	✓
District Controls \times Month f.e.	✓	✓	✓	✓	✓	✓

Notes: The table shows adoption dependence on initial conditions at the district level. The specification estimated is equation 9. In the first row, I_d is a dummy if a district had a positive adoption level before the demonetization. In the second row, I_d the total amount of transactions before the demonetization. In Columns (1)-(2), the dependent variable is the log of the total amount (in Rs.) of transactions carried out using digital wallet in district d during month t ; in Columns (3)-(4), the dependent variable is the log of the total number of active retailers using digital wallet in district d during month t ; in Columns (5)-(6), the dependent variable is the log of the total number of new retailers joining the digital wallet in district d during month t . District-level controls include (log) pre-shock banking deposits, share of villages with ATM facilities, share of villages with banking facility, share of rural population and level of population in the district. Standard errors are clustered at the district level. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table D.5: District adoption rates based on initial adoption: Alternative specification

	log(amount)			log(# users)			log(# switchers)		
	$\delta = 200$	$\delta = 300$	$\delta = 400$	$\delta = 200$	$\delta = 300$	$\delta = 400$	$\delta = 200$	$\delta = 300$	$\delta = 400$
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
(Distance To Hub $> \delta$ km.) $\times \mathbf{1}_{\{t \geq t_0\}}$	-1.309*** [0.374]	-1.129*** [0.357]	-1.113*** [0.345]	-0.537*** [0.182]	-0.499*** [0.151]	-0.482*** [0.138]	-0.358** [0.143]	-0.357*** [0.116]	-0.360*** [0.108]
Observations	6,846	6,846	6,846	6,846	6,846	6,846	6,846	6,846	6,846
R-squared	0.886	0.886	0.886	0.912	0.912	0.912	0.871	0.871	0.871
District f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓
Month f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓
District Controls \times Month f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓
State \times Month f.e.	✓	✓	✓	✓	✓	✓	✓	✓	✓

Notes: The table shows difference-in-differences estimate of the effect of initial conditions, using distance to the nearest hub (defined as districts with greater than 500 retailers in September 2016) as a proxy for the initial share of adopters. The specification estimated is equation 10, replacing D_d with a dummy for distance to hub based on threshold δ ($\mathbf{1}_{\{\text{Distance To Hub} > \delta \text{ km.}\}}$). The dependent variable is either the or the log of the total nominal value of transactions; log of total number of active firms; log of total number of new firms on the digital wallet. District-level controls include (log) pre-shock banking deposits, share of villages with ATM facilities, share of villages with banking facility, share of rural population, level of population, distance to state capital and employment rate in the district. Standard errors are clustered at the district level. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table D.6: Firm adoption based on existing adoption rate (district-level)

	(1)	(2)	(3)	(4)
$x_{i,k,d,t} = \log(\text{amount})_{i,k,d,t}$				
$x_{i,k,d,t-1}$	0.572*** (0.0100)	0.474*** (0.0108)	0.420*** (0.0108)	0.410*** (0.0105)
$X_{k,d,t-1}$	0.0696*** (0.00257)	0.117*** (0.00662)	0.0295*** (0.00439)	0.00606*** (0.00134)
R ²	0.398	0.437	0.459	0.463
$x_{i,k,d,t} = \log(\# \text{ transactions})_{i,k,d,t}$				
$x_{i,k,d,t-1}$	0.776*** (0.0101)	0.709*** (0.00933)	0.635*** (0.0149)	0.624*** (0.0148)
$X_{k,d,t-1}$	0.0237*** (0.00821)	0.0600** (0.0301)	0.116*** (0.00693)	0.0212*** (0.00205)
R ²	0.598	0.615	0.635	0.637
$x_{i,k,d,t} = \mathbf{1}\{\text{On platform}\}_{i,k,d,t}$				
$x_{i,k,d,t-1}$	0.528*** (0.00828)	0.408*** (0.00931)	0.378*** (0.00857)	0.370*** (0.00849)
$X_{k,d,t-1}$	0.0158*** (0.00131)	0.0314*** (0.00180)	0.0198*** (0.00202)	0.00489*** (0.000938)
R ²	0.369	0.419	0.433	0.437
Firm F.E.		✓	✓	✓
District \times Week F.E.			✓	✓
Industry \times Week F.E.				✓
Observations	58,022,429	58,022,429	58,021,662	58,021,662

Notes: The table reports estimates of the dependence of firm-level adoption rates on the share of other adopters in the industry/district. The specification we estimate is a version of equation 12 at *district-level* in which each coefficient is interacted with a weekly dummy; we reported estimates of the coefficient γ . The top panel reports effects when x is the total value of transactions, the middle panel reports effects when x is the total number of transactions, and the bottom panel reports effects when x is a dummy for whether the firm used the platform over the past week. Standard errors are clustered at the district level. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table D.7: Firm adoption based on existing adoption rate (allowing for spillovers across industries)

	(1)	(2)	(3)	(4)
$x_{i,p,d,t} = \log(\text{amount})_{i,p,d,t}$				
$x_{i,p,d,t-1}$	0.533*** (0.006)	0.444*** (0.005)	0.375*** (0.004)	0.358*** (0.003)
$X_{p,d,t-1}$	0.076*** (0.002)	0.135*** (0.002)	0.023*** (0.002)	0.016*** (0.001)
R ²	0.364	0.402	0.432	0.441
$x_{i,p,d,t} = \log(\# \text{ transactions})_{i,p,d,t}$				
$x_{i,p,d,t-1}$	0.711*** (0.005)	0.621*** (0.005)	0.586*** (0.005)	0.579*** (0.005)
$X_{p,d,t-1}$	0.022*** (0.001)	0.043*** (0.001)	0.021*** (0.001)	0.013*** (0.001)
R ²	0.548	0.573	0.585	0.590
$x_{i,p,d,t} = \mathbf{1}\{\text{On platform}\}_{i,p,d,t}$				
$x_{i,p,d,t-1}$	0.496*** (0.007)	0.381*** (0.003)	0.334*** (0.003)	0.323*** (0.003)
$X_{p,d,t-1}$	0.035*** (0.002)	0.071*** (0.001)	0.027*** (0.001)	0.015*** (0.001)
R ²	0.347	0.398	0.420	0.428
Firm F.E.		✓	✓	✓
Industry \times Week F.E.			✓	✓
District \times Week F.E.				✓
Observations	11,750,558	11,750,558	11,750,558	11,749,732

Notes: The table reports estimates of the dynamic specification for adoption based on : $x_{i,p,d,t} = \alpha_i + \alpha_{dt} + \rho x_{i,p,d,t-1} + \gamma X_{p,d,t-1} + \epsilon_{i,p,d,t}$ allowing for spillovers across industries within the same pincode. we reported estimates of the coefficient γ . The top panel reports effects when x is the total value of transactions, the middle panel reports effects when x is the total number of transactions, and the bottom panel reports effects when x is a dummy for whether the firm used the platform over the past week. Standard errors are clustered at the pincode level. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table D.8: Consumption responses across categories based on exposure to the shock

	Necessary	Unnecessary	Bills and Rent	Food	Recreation
	(1)	(2)	(3)	(4)	(5)
$(\text{Exposure})_d \times \mathbf{1}(t = t_1)$	-0.174*** (0.0573)	-0.211** (0.0987)	0.250 (0.268)	-0.185*** (0.0595)	-0.996** (0.431)
Household f.e.	✓	✓	✓	✓	✓
Survey-time f.e.	✓	✓	✓	✓	✓
District Controls \times Survey-time f.e.	✓	✓	✓	✓	✓
Household controls \times Survey-time f.e.	✓	✓	✓	✓	✓
Observations	564,690	564,690	564,690	564,690	564,690
R-squared	0.731	0.622	0.700	0.684	0.460

Notes: The table shows the difference-in-differences estimate for consumption responses across various categories for each event-time after the demonetization shock relative the pre-period (four event-time). The specification estimated is equation 17. The treatment variable is our measure of Exposure_d for the district (as described in Section 2). The dependent variable $\log(y_{h,d,t})$ is either the log of consumption of necessary goods (Column (1)); the log of consumption of unnecessary goods (Column (2)); log of expenditure on bills and rent (Column (3)); the log of expenditure on food (Column (4)); the log of expenditure on recreation activities (Column (5)) as defined in Section 6. District-level controls include (log) pre-shock banking deposits, share of villages with ATM facilities, share of villages with a banking facility, share of rural population and level of population in the district. Household-level controls include pre-shock income and age of head of the household. Standard errors are clustered at the district level. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table D.9: Consumption responses based on alternative cutoff for exposure to the shock

	log(Expense)		
	Total	Necessary	Unnecessary
	(1)	(2)	(3)
$\mathbf{1}_{\{t=t_1\}} \times (\text{Top 25\% Exposure})_d$	-0.0577** (0.0234)	-0.0427* (0.0230)	-0.0781** (0.0343)
$\mathbf{1}_{\{t=t_2\}} \times (\text{Top 25\% Exposure})_d$	-0.0199 (0.0296)	-0.0172 (0.0266)	-0.0277 (0.0454)
$\mathbf{1}_{\{t=t_3\}} \times (\text{Top 25\% Exposure})_d$	0.0146 (0.0370)	-0.00438 (0.0307)	0.0519 (0.0533)
$\mathbf{1}_{\{t=t_4\}} \times (\text{Top 25\% Exposure})_d$	-0.0187 (0.0588)	-0.0588 (0.0580)	0.0374 (0.0786)
Household f.e.	✓	✓	✓
Survey-time f.e.	✓	✓	✓
District Controls \times Survey-time f.e.	✓	✓	✓
Household controls \times Survey-time f.e.	✓	✓	✓
Observations	564,690	564,690	564,690
R-squared	0.706	0.731	0.622

Notes: The table shows difference-in-differences estimate for consumption responses for each event-time post the demonetization shock relative the pre-period (four event-time). The specification estimated is equation 17. Treatment variable takes the value of 1 if our measure of Exposure_d for the district (as described in Section 2) is in the top 25% value of exposure. The dependent variable $\log(y_{h,d,t})$ is either log of total consumption (Column (1)); log of consumption of necessary goods (Column (2)); log of consumption of unnecessary goods (Column (3)) as defined in Section 6. District-level controls include (log) pre-shock banking deposits, share of villages with ATM facilities, share of villages with banking facility, share of rural population and level of population in the district. Household-level controls include pre-shock income and age of head of the household. Standard errors are clustered at the district level. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.

Table D.10: Heterogeneous consumption responses by district's exposure to alternate payment system

	Total		Necessary		Unnecessary	
	(1)	(2)	(3)	(4)	(5)	(6)
$1(t = t_1) \times (\text{Exposure})_d$	-0.303*** (0.0771)		-0.298*** (0.0740)		-0.280** (0.121)	
$1(t = t_2) \times (\text{Exposure})_d$	-0.177* (0.0972)		-0.201** (0.0889)		-0.114 (0.157)	
$1(t = t_3) \times (\text{Exposure})_d$	0.103 (0.131)		0.0199 (0.108)		0.275 (0.203)	
$1(t = t_4) \times (\text{Exposure})_d$	0.121 (0.212)		-0.124 (0.182)		0.445 (0.319)	
$1(t = t_1) \times 1(\text{ATM})_d$	-0.118* (0.0615)	-0.0506* (0.0298)	-0.127** (0.0518)	-0.0491** (0.0241)	-0.0917 (0.0963)	-0.0413 (0.0463)
$1(t = t_2) \times 1(\text{ATM})_d$	-0.148** (0.0663)	-0.0535* (0.0302)	-0.157*** (0.0584)	-0.0528** (0.0253)	-0.116 (0.105)	-0.0438 (0.0490)
$1(t = t_3) \times 1(\text{ATM})_d$	-0.0431 (0.0731)	0.0000 (0.0315)	-0.0481 (0.0615)	-0.0105 (0.0282)	-0.0118 (0.118)	0.0356 (0.0486)
$1(t = t_4) \times 1(\text{ATM})_d$	0.117 (0.114)	0.0644 (0.0604)	-0.0285 (0.0968)	-0.00480 (0.0516)	0.299* (0.174)	0.145* (0.0864)
$1(t = t_1) \times (\text{Top 25\% Exposure})_d$		-0.106*** (0.0318)		-0.104*** (0.0291)		-0.102** (0.0510)
$1(t = t_2) \times (\text{Top 25\% Exposure})_d$		-0.0782** (0.0375)		-0.0829** (0.0335)		-0.0666 (0.0609)
$1(t = t_3) \times (\text{Top 25\% Exposure})_d$		0.00985 (0.0478)		-0.0126 (0.0385)		0.0669 (0.0761)
$1(t = t_4) \times (\text{Top 25\% Exposure})_d$		0.0227 (0.0914)		-0.0993 (0.0776)		0.211 (0.137)
$1(t = t_1) \times (\text{Exposure})_d \times 1(\text{ATM})_d$	0.185* (0.102)		0.217** (0.0987)		0.129 (0.151)	
$1(t = t_2) \times (\text{Exposure})_d \times 1(\text{ATM})_d$	0.232* (0.119)		0.261** (0.112)		0.167 (0.185)	
$1(t = t_3) \times (\text{Exposure})_d \times 1(\text{ATM})_d$	0.0744 (0.142)		0.0724 (0.116)		0.0536 (0.226)	
$1(t = t_4) \times (\text{Exposure})_d \times 1(\text{ATM})_d$	-0.139 (0.218)		0.0818 (0.202)		-0.454 (0.326)	
$1(t = t_1) \times (\text{Top 25\% Exposure})_d \times 1(\text{ATM})_d$		0.0913** (0.0437)		0.114*** (0.0423)		0.0479 (0.0645)
$1(t = t_2) \times (\text{Top 25\% Exposure})_d \times 1(\text{ATM})_d$		0.101* (0.0520)		0.116** (0.0470)		0.0628 (0.0811)
$1(t = t_3) \times (\text{Top 25\% Exposure})_d \times 1(\text{ATM})_d$		0.00388 (0.0600)		0.0110 (0.0494)		-0.0363 (0.0933)
$1(t = t_4) \times (\text{Top 25\% Exposure})_d \times 1(\text{ATM})_d$		-0.0622 (0.0994)		0.0771 (0.0949)		-0.289* (0.148)
Observations	554,894	554,894	554,899	554,899	554,899	554,899
R-squared	0.704	0.704	0.730	0.730	0.618	0.618

Notes: The table shows triple-difference estimate for consumption responses for each event-time post the demonetization shock relative the pre-period (four event-time), based on district's access to ATM facility. Treatment variable is our measure of Exposure_d for the district (odd columns) and takes the values of 1 if the measure of Exposure_d is in the top quartile of the distribution (even columns). $1(\text{ATM})_d$ takes the values of 1 if the number of ATM per capita in district is above the median of the distribution. The dependent variable $\log(y_{h,d,t})$ is either log of total consumption (Column 1-2); log of necessary consumption (Column 3-4); log of unnecessary consumption (Column 5-6). as defined in Section 6. District-level controls include (log) pre-shock banking deposits, share of villages with ATM facilities, share of villages with banking facility, share of rural population and level of population in the district. Household-level controls include pre-shock income and age of head of the household. Standard errors are clustered at the district level. *** : $p < 0.01$, ** : $p < 0.05$, * : $p < 0.1$.