

Can Digital Payment Adoption Reduce Crime?:

Empirical Evidence from India

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Abstract

The introduction of Unified Payments Interface (UPI) in 2016 transformed the digital payments landscape in India. We utilize district-level variation in UPI adoption through differential timings of district ‘lead banks’ joining the UPI platform to study the effects of digital payments on crime. We employ a Difference-in-Difference strategy to test our hypothesis that UPI adoption is negatively associated with the incidence of economic crimes such as robbery and burglary. We explain our hypothesis through the channels of decreased cash availability and an income effect. Our results show that treatment districts which adopted UPI earlier experienced lower economic crime but had no difference in non-economic crime compared to their control counterparts. Robustness tests which restrict our sample to districts with higher mobile ownership show an even greater decrease in crime, providing support for hypothesized channels. Our research contributes to the literature examining the social and developmental consequences of financial inclusion and digital payments.

Keywords: UPI, economic crime, lead bank, robbery.

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1 Introduction

In 2016, the *National Payments Corporation of India* (NPCI) launched the Unified Payments Interface (UPI)— a real-time payment system facilitating inter-bank peer-to-peer and person-to-merchant transactions. The system operates through any UPI client mobile application, where users can link multiple bank accounts and transfer or request funds using their unique UPI ID and registered mobile number. With 622 banks offering UPI services and 16 billion transactions amounting to 23.5 trillion rupees in October 2024 alone (NPCI 2024), UPI has made India a leader in the digital payments ecosystem.

Our paper is set against the backdrop of this increasing UPI uptake as well as demonetization— where the Government of India removed the legal tender status of notes of denomination Rs. 200 and Rs. 500 in an attempt to counter ‘black money’ and the shadow economy. We specifically explore the effect of UPI uptake on crime. There was a pilot launch of UPI in 2016 and this coincided with the timeline for demonetization. Motivated by the findings of Zhao and Huang (2023) investigating the relationship between mobile payments and crime in China, this paper seeks to explore whether districts with a higher UPI uptake have lower rates of crime, specifically economic crime.

We use a Difference-in-Difference design to study this hypothesis. It is inspired by the work of Dubey and Purnanandam (2023) who classify districts into two groups - early and late adopters - based on whether the ‘Lead Bank’ in a district, ascertained by the *Reserve Bank of India* (RBI), was an early adopter of UPI. This helps us create two groups of control and treatment. This decision by banks is taken at the national level so, it is unlikely to be correlated with specific district characteristics, making the assignment quasi-random. We measure the outcome of crime, specifically economic crimes— robbery, burglary and theft— in pre and post periods, with robbery as our main outcome of interest.

As hypothesized, we find a negative impact of UPI uptake on crime. Parallel pre-trends hold for robbery and burglary and both have negative coefficients. Districts which are early

adopters of UPI (treatment group) have on average -0.43 fewer robberies per lakh¹ population in the post period than the expected mean change. This result is economically significant since it represents a 17.9% reduction in robberies from the pre-period sample mean. The fact that the effect is negligible on the non-economic crime of murder further strengthens our hypothesis that this reduction is due to changes in economic and financial variables.

We also run a robustness check by restricting the sample to districts with high mobile penetration (75th percentile and above). These districts will have a higher uptake of UPI and hence should see a higher negative effect on the rate of economic crime. We find that this is indeed the case. The coefficient for robbery in this case is -1.24 as compared to -0.43 in our results and it becomes statistically significant at the 1% level. Additionally, the burglary coefficient becomes significant at the 5% level.

We attribute these results to two primary channels: an increase in formal savings which decreases cash holdings and an increase in income. Bachas et. al (2021) find that providing debit cards increases savings (overall and formal) through channels of reduced transaction costs and increased trust due to regular bank balance validation. We hypothesize these channels to hold true in the case of UPI as well. Informal savings are increased and cash holdings are reduced which reduces economic crime (Armey et al. 2014). Dubey and Purnanandam (2023) find income effects of increased digital payments (adoption of UPI). This increased income leads to an ‘income effect’ that reduces crime (Becker, 1968). We substantiate these channels further in the literature review section.

Demonetization is an important phenomenon to be considered in our results. We find that post-demonetization, economic crimes in districts increased due to the impact it had on reducing household savings (due to the high conversion costs) and household incomes (Krishnan et al. 2017). This effect is however counteracted by the positive effects of UPI in treatment districts that overall, decreases economic crime. Hence, we see differential trends

¹1 lakh = 1,00,000

in crime in our control and treatment districts in the post-period.

Our paper is relevant for policymakers because it examines the positive externality associated with UPI adoption. The fact that it is an externality related to crime is all the more important because of the immense economic impact of crime. Some measures find that the cost of crime is about 2% of the USA's GDP (Chaffin 2015). In a developing country like India, these costs and the cost of controlling crime can be higher. Additionally, crime is an understudied topic in the Indian context even though it is an important determinant of standard of living. Economic crimes also affect efficient allocation of resources, investment flows and economic vitality of small businesses. Our paper adds to the literature across these strands and highlights the (positive) unintended consequences of policy.

2 Background

This paper is set against the background of expanding UPI adoption and demonetization. There has been a push for UPI adoption by the Government of India, after its pilot launch in April 2016. Firstly, every Indian resident received a unique identification card, the Aadhaar Card, as part of a nationwide initiative beginning in 2010. Subsequently, Pradhan Mantri Jan-Dhan Yojana (JDY), a universal banking program aimed at granting a bank account to every household in the nation (Chopra et. al. 2017) was rolled out in 2014. Thirdly, significant resources were allocated to develop the necessary digital infrastructure for a secure and efficient payment system spanning multiple platforms (Acharya 2023). In addition to this development of digital infrastructure, various advertisement campaigns were rolled out to increase adoption. Demonetization in 2016 is a significant event in the context of our paper. It affects both UPI adoption and crime. It positively affects UPI adoption while negatively affecting crime which affects our results (detailed analysis in the discussion section). Moreover, economic crime also remained high with a PricewaterhouseCoopers (PwC) report published in 2016 finding that 31% of respondents from India reported having experienced economic crime in the past 2 years.

2.1 Review of Literature

Our paper is motivated by the findings of Zhao and Huang (2023) who present evidence on the relationship between mobile payments and crime in China. A 2016 policy change in China created a national-level expansion in mobile payments. Utilizing the variation in mobile payment usage across prefectures, Zhao and Huang compare crime-related outcomes through a difference-in-differences empirical strategy. They find that increases in mobile payments have significant negative impacts on crime. Specifically, they distinguish between economic crimes such as theft, burglary and robbery and non-economic crimes such as homicide, finding that the intensity of digital payment usage is effective only in reducing economic crimes but has zero effects on non-economic crimes. Their results show that in regions more exposed to digital payments, the number of criminal cases of theft per 10,000 inhabitants decreased (on average) by roughly 15% of the sample mean. The authors explain these significant findings through the primary channel of ‘decreased cash holdings’ resulting from an increase in mobile payment usage. Individuals prefer to place their income in formal savings institutions such as banks in order to utilize mobile payment systems, therefore reducing the cash kept on-person or in their private properties. This reduces the expected returns from crimes such as theft, robbery and burglary and hence, reduces the incidence of economic crime. Using this literature as motivation we partly explain our findings through the cash channel.

Bachas et al. (2021) find that a scheme that provides debit cards to cash transfer beneficiaries (who own bank accounts) increases both overall and formal savings. The two channels identified for these results are decreased transaction costs and reduced indirect costs of checking bank balances. In essence, the large networks of ATMs reduce the transaction costs of accessing money once deposited into banks and hence increases formal savings. Secondly, the reduction in indirect costs of checking bank balances enables individuals to verify that banks are not unexpectedly reducing balances, creating trust in the banks and banking systems. These channels, especially the former, are relevant to UPI. In a country like India with a large population and geographical variation, the average distance to a bank branch is high. UPI payments facilitate ease in transactions as individuals do not have to go to bank

branches to transact. It also reduces the speed of transactions. With regards to the latter channel, UPI apps like Paytm, PhonePe, Google Pay, etc. have a feature where an individual can check their bank balance. While this feature can lead to increased trust in banks, it cannot be claimed with certainty ex-ante as the adoption of UPI itself can be driven by a channel of trust, leading to reverse causality and self-selection bias. The overall increase in formal savings results in less cash being stored at homes, in-person and in circulation within the economy.

Various studies have established a link between cash and crime. Wright and co-authors (2017) find that a reduction in the circulation of cash via an Electronic Benefit Transfer reduces overall crime rate by 9.2%. They also note that the overall decrease in crime in the United States coincides with periods of decline in the proportion of financial transactions in cash. In our paper, the reduced volume of cash reduces the risk of crimes like robbery, burglary and theft. Armev et al. (2014) revealed a significant association between electronic payments and reduced economic crimes such as robbery and burglary but find limited impact on non-economic crimes like homicide and rape. We similarly examine the effect on these economic crimes as compared to non-economic crimes like murder to examine the strength of our cash channel, since reduced cash in circulation should ex-ante not have any impact on a crime like murder which is usually committed for alternate reasons. Increased cashless transactions also have a dampening impact on crimes like corruption as explored by Setor et al. (2021). However, we limit our analysis to economic crimes reported in the National Crime Records Bureau database (which excludes corruption) due to a lack of reliable reporting.

Dubey and Purnanandam (2023) find income effects of increased digital payments (adoption of UPI). A doubling of digital payment leads to 6.2% higher income. According to economic theory, this ‘income effect’ reduces the economic incentive for crime (Becker, 1968). This effect of UPI adoption is our second channel that leads to a decrease in crimes. Thus, a combination of economic effects namely increased (formal) savings and income results in lower economic crimes.

This leads to the natural question: why study the effect of UPI on crime and not on these economic outcomes? We choose to study the impact on crime firstly, because crime itself has large economic costs, especially in developing countries. Substantiating the economic effect of crime, Detotto and Otranto (2010) likened it to a tax on the economy that reduces domestic and foreign investment, creates inefficient allocation of resources and reduces a firm’s competitiveness. By some measures, in the United States, the cost of crime, narrowly constructed, is about 2% of GDP while other measures find it to be 6% of GDP (Chafin 2015). In addition to the direct economic consequences of crimes, there is also significant spending on crime control.

If the link between UPI uptake and crime can be established, it can lead to more informed policy decisions on the subject. Additionally, crime itself is an understudied topic in India. Studying it as an externality, or an unintended consequence of a policy (UPI uptake) is novel and deserves its own strand of research. We believe that our results are relevant to economies facing the twin phenomenon of high levels of crime and greater adoption of digital payments. A relationship between these two phenomena shows evidence of the supporting role that financial inclusion (through digital payments) plays in deterring crime and improving developmental outcomes. With the advent of UPI in 2016, India’s economy has undergone a major digital payments revolution. Alongside its economic implications, the effect of UPI on social and developmental outcomes, like crime, is a relevant and necessary area of research.

2.2 Data and Descriptive Statistics

Our outcome crime variables — robbery, theft, burglary and crime — are obtained from the ‘Crime in India’ report released by the National Crime Records Bureau (NCRB) every year, which provides district-level data on all crimes booked under the Indian Penal Code. To account for socioeconomic factors and population demographics, we collect data at the district level from the 2011 Census. Since there are discrepancies in district names and boundaries in the NCRB dataset and the 2011 Census, we use data downloaded from

Ashoka University's *Centre for Economic Data and Analysis* (CEDA) Data Portal which contains crime data matched to census districts. These variables are defined in Table 1 and their summary statistics are provided in Table 2.

Table 1: Definition of variables

Variable	Definition	Data Sources
theft	Number of theft cases (as per IPC section 390) per lakh population in a district	NCRB (through CEDA Data Portal)
robbery	Number of robbery cases (as per IPC section 390) per lakh population in a district	NCRB (through CEDA Data Portal)
burglary	Number of burglary cases (as per IPC section 443) per lakh population in a district	NCRB (through CEDA Data Portal)
murder	Number of murder cases (as per IPC section 302) per lakh population in a district	NCRB (through CEDA Data Portal)
literate	Share of literate population in a district	Census 2011
ruralHHshare	Share of rural households in a district	Census 2011
mobileHHshare	Share of households in a district with mobile ownership	Census 2011
internetHHshare	Share of households in a district with internet access	Census 2011

Table 2: Summary Statistics by Districts with Early and Late UPI Adoption by Lead Banks

	Mean	SD	Min	Max	N
Early UPI Adopting Districts					
Theft	31.73	80.83	0.00	1615.42	815
Robbery	2.21	5.40	0.00	88.45	815
Burglary	6.38	7.82	0.00	86.23	815
Murder	2.49	1.82	0.00	17.06	815
Literate Population Share	0.64	0.10	0.40	0.89	815
Share of Rural Households	0.67	0.21	0.00	0.93	815
Share of Households with Internet	0.02	0.03	0.00	0.17	815
Share of Households with Mobile	0.39	0.09	0.16	0.58	815
Late UPI Adopting Districts					
Theft	35.74	115.42	0.00	2090.03	2325
Robbery	2.19	4.76	0.00	86.00	2325
Burglary	6.93	10.02	0.00	140.39	2325
Murder	2.52	1.58	0.00	34.08	2325
Literate Population Share	0.62	0.10	0.29	0.87	2325
Share of Rural Households	0.75	0.20	0.00	1.00	2325
Share of Households with Internet	0.01	0.02	0.00	0.17	2325
Share of Households with Mobile	0.36	0.10	0.01	0.63	2325
Total					
Theft	34.70	107.52	0.00	2090.03	3140
Robbery	2.20	4.93	0.00	88.45	3140
Burglary	6.79	9.50	0.00	140.39	3140
Murder	2.51	1.64	0.00	34.08	3140
Literate Population Share	0.62	0.10	0.29	0.89	3140
Share of Rural Households	0.73	0.21	0.00	1.00	3140
Share of Households with Internet	0.02	0.02	0.00	0.17	3140
Share of Households with Mobile	0.37	0.10	0.01	0.63	3140

Note: The crime variables (theft, robbery, burglary and murder) are cases per lakh population.

Source: Crime variables - NCRB sourced from CEDA. District Characteristics - 2011 Census

3 Empirical Strategy

Our identification strategy is motivated by Dubey and Purnanandam (2023) who study the impact of UPI adoption on household income and small business activities. Their novel strategy utilizes differences in the timing of participation on the UPI platform by different banks to establish a causal link between digital payments and economic outcomes. Our strategy is similarly based on the variation in the timing of exposure to UPI payments across districts based on when the ‘lead bank’ of a district decided to participate in the UPI system.

The ‘Lead Bank’ system was established by the Reserve Bank of India in 1969 on the recommendations of the Gadgil Study Group which provided plans to improve access to banking and credit structures in rural areas (RBI 2016). Due to a lack of commercial bank presence and orientation towards rural areas, these public-sector lead banks present in all districts are tasked with the objectives of improving banking access and financial services to underserved communities. Hence, the specific policies adopted by public-sector banks (eg. whether to participate in UPI) have significant effects on the extent and nature of financial inclusion experienced by the populations residing in the districts where the bank is the ‘lead bank’.

When UPI was introduced in August 2016, 29 banks indicated their interest in joining the new platform. 21 of them joined the platform immediately, while the other 8 joined by the end of November 2016. However, within these ‘early-mover’ government banks, there were some which were notably missing from the list given their large market share. For customers of these banks, this posed a barrier to them adopting digital payments even if they wished to do so. By May 2017, even the other ‘late adopter’ banks had joined the platform.

3.1 Difference-in-Differences

Why do we not do a simple difference (pre-post 2016) to estimate the impact of digital payment adoption on crime? It could have been that people started using UPI in response to an increase in cases of theft/robbery/burglary and this implied reverse causality would lead to an exaggeration of our studied effect. To deal with such endogeneity issues, we use

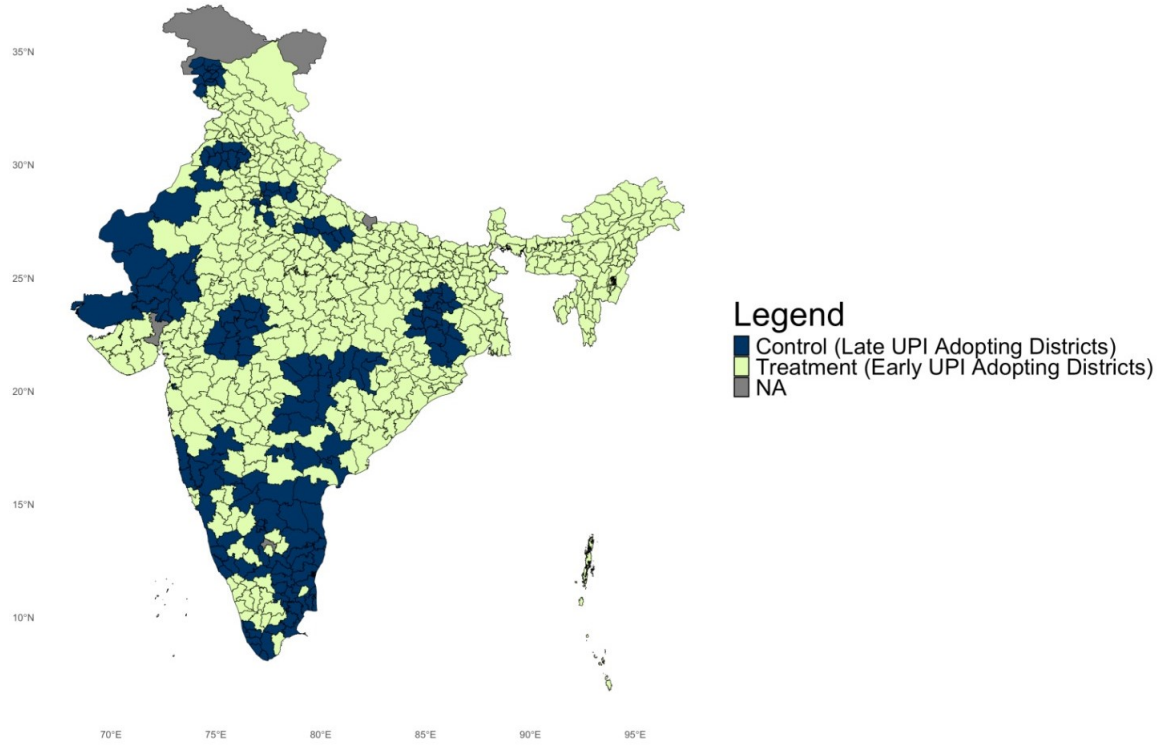


Figure 1: India Map showing Districts whose Lead Bank adopted UPI Early vs Late

the differential adoption of UPI by lead banks as an exogenous policy ‘shock’ unrelated to crime but leading to variations in digital payment access across districts.

For our difference-in-differences method, we utilize variation in the timing of lead banks participating in the UPI scheme to construct our treatment group (which consists of districts that were early adopters) and control group (late adopters) to find the impact of UPI adoption on economic crimes such as theft, robbery and burglary. One of the main assumptions of our identification strategy is that the pre-trends in our crime rates of interest are ‘parallel’. Thus, the changing differential in crime rates between treatment and control groups can be solely attributed to the UPI shock. We discuss parallel pre-trends and threats to this identification strategy in the next sections.

3.2 Estimating Equations

Our empirical specification to measure the difference-in-difference estimate is the following:

$$Y_{it} = \beta_0 + \beta_1 * Treat \times Post + \beta_2 * X'_{it} + \mu_i + year_t + \varepsilon_{it} \quad (1)$$

Here i and t index districts and time respectively. Our outcome variable Y_{it} is different crime indicators like robbery, theft, burglary and murder in district i at time t . $Treat$ is a binary variable which takes the value 1 for early UPI-adopting districts and 0 for late adopters. $Post$ is also a dummy which takes the value 1 for years post 2016 and 0 otherwise. X'_{it} are our covariates, and ε_{it} is the error term. μ_i and $year_t$ are district-level and time-fixed effects, respectively.

The district-level fixed effects washes away all time-invariant differences across districts (for example: location of the district) in our sample while the time-fixed effects controls for factors which are constant across districts but vary over time (for example: national-level policies). Including these fixed effects is one reason why we can afford to have few covariates, and why the controls we have included may not show significant coefficients. This is also why we do not separately have the treatment and post dummies since these are differenced away.

The β_1 coefficient in Equation (1) can be interpreted as the Average Treatment Effect on Treated or the DiD estimate, after accounting for various controls and fixed effects. We expect the β_1 coefficient to be negative if our hypothesis, that the introduction of UPI payments reduced economic crime, stands true.

4 Results

4.1 Verifying Parallel Trends

Our figure 2 provides a visual representation of the trends for the robbery variable in the pre-period. Visually, parallel pre-trends can be observed for the period from 2014 to 2016 (pre-treatment year) providing evidence for the hypothesis of no differential growth rates of robbery for treatment and control districts. In the post-period, we can visually verify that the control group witnesses a change in growth rates (becomes stagnant and then rises) while the treatment group witnesses a continued negative trend. In Table 2 3 we can see that the coefficients for the year (2014, 2015) interacted with treatment are statistically

Table 3: Results of Parallel Trends Check

	(1)
	Robbery
	b/se
Treat \times year=2014	-0.05 (0.24)
Treat \times year=2015	0.24 (0.24)
Control Variables	YES
District Fixed Effects	YES
Year Fixed Effects	YES
Observations	1886

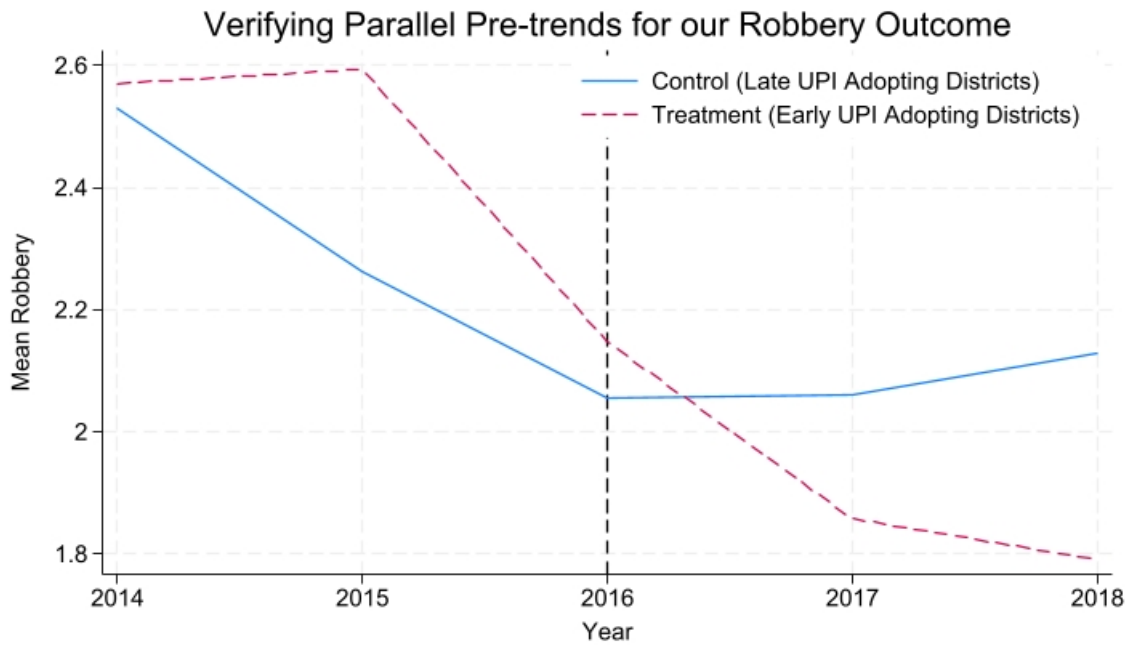


Figure 2: Parallel Trends

insignificant, verifying parallel pre-trends. Similarly, parallel pre-trends hold for burglary but not for theft and murder. (Can be visually ascertained from graphs in our appendix)

4.2 Baseline Estimates

Table 4: Estimated Effects of UPI adoption on Crime

	(1)	(2)	(3)	(4)	(5)
	Robbery	Robbery	Theft	Burglary	Murder
	b/se	b/se	b/se	b/se	b/se
Treat*Post	-0.43** (0.19)	-0.43** (0.19)	-1.08 (3.04)	-0.54 (0.44)	0.00 (0.08)
Population		-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)	-0.00 (0.00)
Literate		0.00 (0.00)	-0.00 (0.00)	0.00 (0.00)	0.00 (0.00)
Rural Household Share		-0.00 (3.35)	-6.40 (52.25)	0.77 (7.63)	-0.75 (1.35)
Internet Household Share		-10.54 (170.32)	152.57 (2653.94)	-97.57 (387.32)	5.94 (68.68)
Mobile Household Share		-3.84 (9.75)	38.05 (151.91)	6.32 (22.17)	1.72 (3.93)
District Fixed Effects	YES	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES	YES
Observations	3140	3140	3140	3140	3140

Results in Table 3 show that the coefficient of the Treat*Post interaction terms when regressed on the outcome variable of Robbery is -0.43 and is statistically significant at the 5% level. This can be interpreted as: Districts which are early adopters of UPI (treatment group) have on average -0.43 less robberies per lakh population in the post period than the expected mean change. This result is economically significant since it represents a 17.9% reduction in robberies from the pre-period sample mean.

Our coefficient estimate for Treat*Post on the outcome variables of Theft (parallel pre-trends do not hold) and Burglary (pre-trends hold) retain the hypothesized negative coefficients but are not statistically significant. Its coefficient on the outcome variable of murder is 0 and hence, shows a zero effect but is statistically insignificant.

The coefficient estimate for Treat*Post when regressed on robberies remains unchanged after

the inclusion of control due to the presence of District-level fixed effects which capture all the time-invariant differences across districts.

4.3 Robustness

Table 5: Estimated Effects of UPI adoption on Crime - Districts with High Mobile Penetration

	(1)	(2)	(3)	(4)
	robberyrobust	theftrobust	burglaryrobust	murderrobust
	b/se	b/se	b/se	b/se
Treat*Post	-1.24***	8.86**	-2.29**	0.05
	(0.43)	(4.13)	(1.12)	(0.09)
District Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Observations	786	786	786	1878

We conduct a robustness test by running our DID only in districts with higher mobile penetration. According to 2011 census data, we choose districts above the 75th percentile (i.e. 45% of mobile penetration in a district). The argument is that UPI uptake will be higher in districts with higher mobile penetration. Hence, if UPI uptake is the channel of crime reduction, we should find a higher negative coefficient in these districts. Post analysis, we find that this is indeed the case. The coefficient for robbery in this case is -1.24 as compared to -0.43 in our results 4 and it becomes statistically significant at the 1% level. This is a 41% reduction. This is quite significant but might be an overestimate given identification issues. Burglary has a larger negative coefficient which is statistically significant at the 5% level. The effect on murder continues to remain insignificant. The effect on theft is surprising as the coefficient increases and is significant. However, as reported earlier, parallel pre-trends do not hold for theft so the coefficient is not relevant. Thus, we conclude that our results in terms of channels are verified through the robustness check.

A potential limitation we find in using this robustness strategy is that the data is 2011 data. Trends in mobile penetration might have changed significantly since then. However, an argument could be made that lead districts would remain so in terms of mobile penetration.

5 Discussion

Our coefficient estimates in Table 3 4 for the $Treat*Post$ variable show statistically significant results only for the Robbery outcome variable and not for other economic crimes of Theft and Burglary. We explain these findings as driven by our primary channel of ‘decreased cash holdings’ due to formal savings since robbery is motivated more by the availability of cash than crimes such as burglary. Theft is defined as the act or intention of dishonestly taking away another’s private property and Robbery is theft while voluntarily causing harm to the victim. Burglary is the act of trespassing on privately owned real estate (Legislative Department). Burglary usually involves house theft of valuables such as expensive assets and metals and hence, is not expected to be motivated primarily by cash availability. This could potentially explain the statistical insignificance of our coefficient on burglary. Robbery on the other hand is more likely to be motivated by cash availability since it usually occurs in settings against individuals (as opposed to real estate).

Most importantly our results show a zero coefficient on Murder which supports our hypothesis that UPI adoption does not have any impact on non-economic crimes. Research shows that the drivers of murder are multifactorial and are caused by psychological, psychopathological, social and developmental factors (Bothelo and Goncalves 2016). Hence, our expectation of a weak or zero effect of UPI adoption (through income or cash channels) on murder is captured by our regression estimate.

The external shock of demonetization which occurred in 2016 adds a new dimension to our results. Demonetization had the impact of reducing household savings (due to the high cash conversion costs) and had a negative impact on household incomes (Krishnan et al. 2017). Through the literature surveyed in the literature review section, this wealth shock and lower savings are correlated with a rise in crimes, especially economic crimes such as robbery, theft and burglary. However, since UPI uptake coincided with demonetization, it counteracted its effects in the treatment group. UPI’s effect on increasing formal savings and income, subsequently reducing crimes counteracted the impacts of demonetization in districts that are early adopters of UPI. This phenomenon can be observed in Figure 2: Parallel Trends 2

since the negative pre-trend for the control group (late UPI adopters) stagnates (and then rises) while the negative trends for the treatment group (early UPI adopters) continue to hold in the post-period as well.

6 Limitations & Future Research

6.1 Threats to Identification

Our identification strategy is driven by classifying districts as early and late adopters based on whether the Lead Bank in the district was an early adopter of UPI or not. This involves two sets of assumptions that need not necessarily hold true. Firstly, it assumes that the lead bank alone (or largely) drives UPI adoption in a district. This might not be the case, especially in districts that have multiple banks such that other banks could be early adopters. In this case, these districts would be coded as late adopters and will bias our coefficients downwards. Secondly, this strategy assumes that if the lead bank is an early adopter then a significant proportion of the population would end up adopting UPI. However, this might not be the case. This means that districts we classify as early adopters are truly late adopters (based on population UPI uptake). This again biases our results downwards. While these are limitations of the identification strategy, they actually strengthen our claims. In this context, our coefficients are the lower bound estimates.

6.2 Other Limitations

Our paper is set against the backdrop of Demonetization. This is an external shock that affected both UPI uptake and crime. In the absence of the shock, it is difficult to claim what results would have been. It is possible that the differences would not be as stark. Additionally, demonetization had differential impacts across different districts that we have not been able to account for. So, this paper might not be generalizable across different countries and economic contexts.

There are several limitations to using the NCRB crime data. Chaudhuri et al. (2014) acknowledge that crime may be severely under-reported. This leads to attenuation bias.

However, if this under-reporting is differential across different districts then the impact cannot be predicted ex-ante.

6.3 Scope for future research

We identify two channels that lead to our results - increased formal savings (lower cash in circulation) and increased income. Though these effects of UPI are found in previous literature, future research could measure these channels along with impacts on crime on the same dataset and time frame to strengthen claims.

There is scope to do a heterogeneity analysis along the lines of intensity of UPI usage among different districts. Additionally, as mentioned in our literature review, cashless transactions affect crimes like corruption as well. Future research could examine other economic crimes like corruption as well, potentially creating an index of economic crimes.

7 Conclusion and Policy Implications

Our paper provides evidence of the association between the introduction of UPI technology in India in 2016 and a decrease in economic crime. These findings have important implications. As national payment systems proliferate across the world, it is important to consider the externalities brought upon by their introduction. For policymakers in the developing world, this evidence helps give impetus to encouraging technological innovation that targets multiple developmental goals like financial inclusion and personal security. Encouraging digital payments not only strengthens financial systems but also improves social welfare and trust (through reduced crime) which has significant positive externalities on the overall growth and development context of a country.

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8 Appendix

Table 6: Summary Statistics of Districts by Pre-Post Period

	Mean	SD	Min	Max	N
Pre-period					
Theft	32.28	84.91	0.00	1437.62	1886
Robbery	2.40	5.70	0.00	88.45	1886
Burglary	7.91	10.24	0.00	140.39	1886
Murder	2.67	1.78	0.00	34.08	1886
Post-period					
Theft	38.34	134.51	0.00	2090.03	1254
Robbery	1.89	3.45	0.00	70.09	1254
Burglary	5.11	7.97	0.00	96.59	1254
Murder	2.27	1.38	0.00	12.19	1254

Parallel Trends Graphs

