Mobile Payments and Crime: Evidence from China*

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Abstract: Using a policy change in 2016 as a natural experiment, we employ a Difference-in-Difference (DID) model to analyze the effects of mobile payments development on crime rates in Chinese prefectures from 2015 to 2019. Our findings indicate that mobile payments expansion has a significant negative effect on theft, with the reduction of residents' cash holdings serving as a potential mechanism. However, we find no significant impact on non-economic crimes like rape and murder. This study provides evidence supporting the role of policies and technologies enabling mobile payments development in deterring crime and enhancing social security.

Keywords: mobile payments; crime; cash; DID method; DDD method

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1. Introduction

Crime poses a substantial threat to public safety, disrupting social order, straining resources, and fostering a widespread sense of insecurity that hampers societal well-being and development. In an era marked by relentless technological advancement, crime has evolved in tandem with the changing technological landscape.

A growing body of literature investigates the nexus between digital payments and criminal activity. Armey et al. (2014) revealed a notable association between electronic payments and reduced economic crimes such as robbery and burglary but found limited impact on non-economic crimes like homicide and rape. Wright et al. (2017) demonstrated that the Electronic Benefit Transfer (EBT) program significantly lowered overall crime rates. Pridemore et al. (2018) showed that decreasing cash usage could substantially reduce street crimes tied to cash, such as theft and robbery. Setor et al. (2021) observed that electronic payments had a significant dampening effect on corruption. However, existing literature has shortcomings in both the coverage and depth of using digital payment, while the recent development of mobile payments in China offers a unique opportunity for an intriguing and comprehensive case study.

Mobile payments have gained immense popularity in China. About 903.6 million people, roughly 64 percent of the overall population, use mobile payments in 2021, making China a pioneer in moving towards a “cashless society”. Scanning Quick Response Code is the most dominant mobile payments technology in China, covering 96% of users in 2021. This technology was pioneered by Alipay in 2011, followed by Tenpay in WeChat in 2013. The fierce competition between these two tech giants drew regulatory scrutiny, resulting in the People's Bank of China taking measures to suspend mobile payments in March 2014. After a comprehensive two-year assessment, the "Barcode Payment Business Specification (Draft Open for Comment)" was issued by the China Payment and Clearing Association, under the central bank's guidance, in August 2016. This release represented the official endorsement of QR code-based mobile payments for widespread use. Consequently, mobile payments have permeated diverse sectors, becoming an omnipresent mode of transaction.

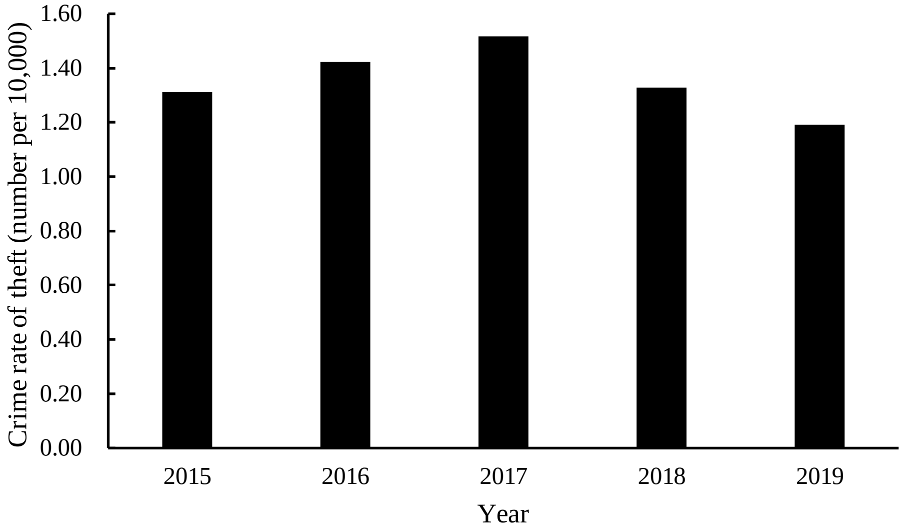

Fig. 1. The verdicts of theft per 10,000 (2015-2019)

The release of the "Specification" in 2016, serving as an external policy shock influencing mobile payments, offers an ideal context for assessing its impacts. This study seizes upon this policy evolution as a natural experiment to gauge the developmental impact of mobile payments. Our primary focus revolves around the influence of mobile payments expansion on crime rates, particularly on theft, a common economic crime in China. We utilize criminal data obtained from China Judgements Online (CJO), a comprehensive source of judicial big data.[1] Our definition of the crime rate entails the number of first-round verdicts in criminal offenses per 10,000 inhabitants. Figure 1 illustrates the theft crime rate in sample cities from 2015 to 2019, computed from our dataset. The average theft rate stood at 1.311 cases per 10,000 inhabitants, displaying a gradual increase from 2015 to 2017, followed by a decline after 2017.

To investigate the potential link between the growth of mobile payments and theft crime rate, we propose two hypotheses. The first examines whether the rapid expansion of mobile payments in China has reduced theft rates. We collect annual crime data from 278 Chinese prefectures between 2015 and 2019, and consider a difference in difference (DID) approach, treating the 2016 "Barcode Payment Business Specification (Draft for Comment)" as an external shock. Our findings reveal that mobile payments have a significant impact in reducing theft rates, particularly in regions with well-established digital finance infrastructure. However, we did not observe any significant effects of mobile payments expansion on non-economic crimes like rape or murder.

Our second hypothesis focus on the role of cash as a facilitator of crime and whether mobile payments, by replacing cash transactions, could deter criminal activities. Cash transactions, due to their liquidity and inherent anonymity, are often associated with predatory crimes (Foley, 2011; Armey et al., 2014; Wright et al., 2017). To investigate this, we use data from the China Household Finance Survey, covering

[1] China Judgments Online was established by the Supreme People's Court of China in 2016, which is the official online platform that publishes all legal judgments.

approximately 40,000 households across 29 provinces. Our findings revealed a notable decrease in household cash reserves due to mobile payments expansion. Furthermore, we employ a triple-difference model to confirm that cities with more cash experienced larger reductions in theft, thus establishing the mechanism through which mobile payments influence theft by affecting household cash holdings.

Our research contributes to several areas existing areas of literature. First, it adds to the growing body of research concerning the economic implications of mobile payments. Prior studies have explored the effects of mobile payments on the well-being of rural residents, particularly females (Zheng & Ma, 2022), changes in savings rates (Zhao & Zhao, 2022), household consumption (Liu et al., 2020; Zhao et al., 2022), and household entrepreneurship (Yin et al., 2019; Wang, 2020). Our investigation unveils that mobile payments exert a broader influence that goes beyond financial transactions, impacting various facets of individuals' lives, including crime rates. Second, our findings align with research by Jiang & Liang (2022), who identified a negative correlation between digital finance and theft-related criminal activities. However, our paper takes a distinct approach by leveraging policy adjustments as exogenous shocks, thereby offering robust evidence of the causal link between mobile payments expansion and crime rate reductions in China. Third, we provide direct empirical evidence confirming that mobile payments expansion reduces cash holdings, subsequently impacting crime rates. Finally, we underscore the valuable insights that can be drawn from China's experience with mobile payments. Given the user-friendly nature and cost-effectiveness of mobile payments using QR code technology, it holds significant potential for rapid adoption in other developing countries, which can play a pivotal role in enhancing social security and stability within these nations.

The rest of this paper is organized as follows. Section 2 provides an overview of the data used in our study and introduce our identification strategy. Section 3 presents our empirical results with robustness verifications. Section 4 discusses the potential mechanisms. And section 5 concludes.

2. Estimation Method and Data

2.1 Data

We have compiled a city-year panel dataset covering 278 cities from 2015 to 2019. Crime data was sourced from China Judgements Online, the official platform for publishing legal judgment documents from all levels of people's courts in China.[1] We manually collected data for each prefecture, and measure the theft crime rate as the number of verdicts for theft-related criminal offenses per 10,000 residents. It's important to clarify that in this study, the term “theft” refers to criminal cases of theft,[2] and the location of the case is the prefecture where the court trial occurred.[3] It's important to note that the verdict documents are based on trial time, resulting in a time lag between the crime activity and legal verdicts. For example, theft cases that occurred in 2016 would typically lead to court verdicts in 2017. As a result, we match the crime

[1] China Judgements Online is accessible at https://wenshu.court.gov.cn/. The retrieval process of the theft case data in this paper can be found in the Table B of appendix.

[2] The criteria for prosecuting theft crimes underwent four revisions, occurring in 1984, 1992, 1998, and 2013, but these adjustments do not affect our sample data. While we acknowledge the existence of unreported criminal cases, often referred to as "black numbers," it's important to note that these cases are typically relatively minor (Skogan, 1977). Therefore, using official records remains a reliable method for measuring the incidence rate (Levitt, 1998).

[3] According to Liang and Jiang (2020), the location of the trial court can reflect the geographical distribution of theft cases.

data with lagged control variables.[1]

We employ the Digital Financial Inclusion Index of China (DFII) developed by Peking University (Guo et al., 2019) as the core measure of digital financial development. This index, developed through a collaboration between the Institute of Digital Finance at Peking University and Ant Financial Services Group of Alibaba, utilizes Alipay data to track digital financial services across three dimensions: coverage, usage depth, and digitalization. The DFII is available at three geographic levels: province, prefecture, and county. Our empirical study primarily use data at the prefecture level. In the mechanism analyze, we also use the payment usage index, a sub-index of DFII. The payment usage index is conducted based on the number of payments per capita, amount of payments per capita and the proportion of number of high-frequency active users (50 times or more each year) to number of users with a frequency at least once each year, which fully reflects the usage of Alipay by individuals. We use the payment usage index at the prefecture level.

To account for socioeconomic factors, we collect data at the prefecture level and introduce the following controlled variables into our regression model, such as education, urban-rural disparities, unemployment rates, urbanization levels, police presence, logarithm GDP per capita, government expenditure, population density, internet coverage, and mobile phone usage. These variables are sourced from the China Statistical Yearbook, Statistical Yearbook of various prefectures and the China City Statistical Yearbook with definitions presented in Table 1 and summary statistics in

[1] In the robustness test of the empirical results, we discuss the plausibility of lagging our data by one period.

Table 2. Our dataset forms a city-level balanced panel dataset, covering 278 cities from 2015 to 2019, totaling 1390 observations.[1]

We further incorporate survey data from the China Household Finance Survey (CHFS), which covers approximately 40,000 households across 29 provinces, municipalities, and autonomous regions in China (excluding Tibet, Xinjiang, Hong Kong, Macao, and Taiwan). The CHFS collects detailed information on household demographics, assets and debts, income and consumption, insurance, and social security, among other pertinent factors. In particular, we employ data from the China Household Finance Survey (CHFS) to empirically examine the mechanism underlying our hypothesis.

Table 1 Definition of variables.

Variable	Definition	Data Sources
Theft rate	The number of first-round verdicts in criminal offences of theft Per 10,000 inhabitants	Authors' calculations
Rape rate	The number of first-round verdicts in criminal offences of rape Per 10,000 inhabitants	Authors' calculations
Murder rate	The number of first-round verdicts in criminal offences of murder Per 10,000 inhabitants	Authors' calculations
DFII	Digital Financial Inclusion Index	Institute of Digital Finance at Peking University
Payment	Payment Usage Index	Institute of Digital Finance at Peking University
Education	The average years of education of the population over 6 years old	China Statistical Yearbook
Urban-rural gap	The ratio of urban residents’ income per capita to rural residents’	Statistical Yearbook of various prefectures

[1] The complete list of cities in our sample can be found in the Table A of appendix.

Unemployment	Urban registered unemployment rate (%)	Statistical Yearbook of various prefectures
Urbanization	The proportion of urban population to the total population	Statistical Yearbook of various prefectures
Police	The share of spending on policing in total government expenditure	China Statistical Yearbook
Ln GDP per capita	Logarithmic value of GDP per capita	China City Statistical Yearbook
Government expenditures	Logarithmic value of government expenditure per capita	China City Statistical Yearbook
Population density	Number of population per square kilometers	China City Statistical Yearbook
Internet	Number of internet users per capita	China City Statistical Yearbook
Mobile phone	Number of mobile phone users per capita	China City Statistical Yearbook

Table 2 Descriptive statistics.

Variable	N	Mean	Std. Dev.	Min	Max
Theft rate	1390	1.311	0.993	0.127	7.230
Rape rate	1080	0.062	0.050	0.001	0.263
Murder rate	1125	0.028	0.031	0.001	0.707
DFII	1390	193.403	37.167	105.610	302.980
Payment	308	213.747	48.810	116.010	375.990
Education	1390	8.974	0.510	7.409	12.068
Urban-rural gap	1390	2.561	0.326	1.845	3.474
Unemployment	1390	3.274	0.572	1.300	4.5000
Urbanization	1390	0.564	0.083	0.400	0.896
Police	1390	0.055	0.010	0.037	0.124
Ln GDP per capita	1390	10.743	0.528	9.227	12.281
Government expenditures	1390	9.072	0.477	7.909	11.642
Population density	1390	433.426	344.203	5.730	2648.110
Internet	1390	0.238	0.178	0.003	1.953
Mobile phone	1390	1.026	0.501	0.111	4.390

2.2 Estimation Method

To quantify the impact of mobile payments development on theft crime rates, we must address several empirical challenges, primarily related to endogeneity. First, measurement errors can introduce bias into our results. Second, crucial variables that influence criminal activities may be omitted from our analysis. Third, reverse causality could exacerbate the endogeneity problem. For instance, if individuals start using mobile payments in response to an increase in theft incidents, any observed negative relationship between crime rates and mobile payments would be exaggerated.

To address these endogeneity issues, we employ a strategy that leverages the release of the "Specification" in 2016 as an exogenous policy change unrelated to crime but resulting in the expansion of mobile payments. We then estimate changes in crime rates using a difference-in-difference (DID) method. However, as the release of the "Specification" applies nationwide to all cities, we do not have natural treatment and control groups for our analysis.

Following Vig (2013), we can construct treatment and control groups by considering their diverse reactions to the release of the "Specification". We argue that cities with more advanced digital financial development in the initial stage will experience more substantial impacts from the policy change and achieve greater progress in mobile payments development. Accordingly, we classify the cities in our dataset into two groups: high and low, based on the median value of the 2016 Digital Financial Inclusion Index for each city. The group consisting of cities with higher digital financial inclusion development is designated as the relative "treatment group", while the group comprising cities with lower digital financial inclusion development is regarded as the relative "control group". It is important to note that when employing this method, the treatment and control groups are "relative" rather than "absolute".

As previously mentioned, the verdict documents are timestamped based on trial time, which aligns with control variables lagged by one period. For instance, judgment documents published in 2016 are associated with control variables from 2015. We further account for time and city-specific factors to setup the following fixed-effect model,

$$crime\_theft_{it} = \alpha + \beta Treat \times Post + \gamma X_{i,t-1} + \mu_i + year_t + \varepsilon_{it} \qquad (1)$$

where *i* indexes cities, *t* indexes time; $crime\_theft_{it}$ denotes the crime rate of theft in city *i* at time *t*; μ_i and $year_t$ are city and year fixed effects, respectively; $Post$ is a dummy variable that equals one for year 2018 onward and zero otherwise.[1] $Treat$ is a dummy variable that equals one if the city belongs to the treatment group (high level of digital financial inclusion development group) and zero if it belongs to the control group (low level of digital financial inclusion development group). $X_{i,t-1}$ are control variables, and ε_{it} is the error term. We cluster standard errors at the city level. The β coefficient in equation (1) can be interpreted as the regression-based DID estimate after accounting for various controls and fixed effects. We expect β to be negative if the development of mobile payments has a reduced crime rate of theft.

3. Empirical Results

[1] The policy shock in 2016 is aligned with crime data from 2017; hence, the post indicator corresponds to 2018 and 2019.

3.1 Baseline Estimates

The empirical results of the difference-in-differences (DID) method are reported in Table 3. The coefficient of the interaction term *Treat*×*Post*, which captures the causal effect of mobile payments development on the crime rate, is -0.1871 in column (1) and -0.2199 in column (2). Both coefficients are statistically significant at the 1% level. These results suggest that the development of mobile payments, as marked by the release of the "Specification", significantly reduce the crime rate of theft in the treatment group (cities with higher levels of digital finance inclusion) compared to the control group (cities with lower levels of digital finance inclusion). On average, the number of criminal cases of theft per 10,000 inhabitants decreased by approximately 0.19 to 0.22, which represents roughly 15% of the sample mean.

Table 3 Estimated effects of mobile payments on theft.

Variable	（1）	（2）
	Crime Rate of Theft	
Treat×Post	-0.1871***	-0.2199***
	(0.0504)	(0.0510)
Education		-0.0857
		(0.0881)
Urban-rural gap		0.6031
		(0.4317)
Unemployment		-0.0028
		(0.0712)
Urbanization		3.9865**
		(1.8505)
Police		16.4681***
		(5.8791)
Ln GDP per capita		0.0275
		(0.1884)
Government expenditures		-0.0998
		(0.1385)

Population density		-0.0002
		(0.0006)
Internet		0.0380
		(0.2056)
Mobile phone		-0.1556
		(0.1595)
City fixed effects	YES	YES
Year fixed effects	YES	YES
R^2	0.1372	0.1699
N	1390	1390

Notes: Robust standard errors in parentheses are clustered at the city level. * significant at 10%; ** significant at 5%; *** significant at 1%. Hereinafter the same.

3.2 Verify Parallel Trend

The parallel trend assumption is crucial to ensure the unbiasedness of the DID estimator. In equation (1), we replace *Treat*×*Post* with interaction terms between Treat and year dummy variables. These interaction terms help us assess whether there exists a significant prior difference in the theft crime rate between the two sample groups, providing a verification of the parallel trend assumption.

Table 4 Results of parallel trends check.

Variable	Crime Rate of Theft
Treat×year2016	0.0801
	(0.0528)
Treat×year2017	0.0639
	(0.0518)
Treat×year2018	-0.1385**
	(0.0638)
Treat×year2019	-0.2074***
	(0.0668)
Control Variables	YES
City fixed effects	YES
Year fixed effects	YES
R^2	0.1728
N	1390

The results in Table 4 show that the estimated coefficients of *Treat*×*year2016* and *Treat*×*year2017* are not significantly different from 0, meaning that prior to the release of the "Specification", the difference in the crime rate of theft between the two groups is insignificant, which satisfies the parallel assumption of DID. The estimated coefficients of *Treat*×*year2018* and *Treat*×*year2019* are significantly negative at the 5% and 1% levels respectively, and the magnitude of these estimated coefficients gradually increase, meaning that the expansion of mobile payments since the release of the "Specifications" has significantly reduced the crime rate of theft, and this effect has been increasing over time. In 2018, the development of mobile payments made the number of criminal theft cases per 10,000 inhabitants in the treatment group (with better digital finance development) changed by -0.139. This effect became even more pronounced in 2019, with a change of about -0.207.

3.3 Robustness

3.3.1 DID with a Continuous Treatment

Given the absence of a clean control group due to the nationwide policy shock, we employ a robustness test following the approach of Nunn and Qian (2011). We consider a Difference-in-Difference model with a continuous treatment, where the digital financial inclusion development index captures the intensity of the impact. We construct the following model:

$$crime\_theft_{it} = \alpha + \beta index_i \times Post + \gamma X_{i,t-1} + \mu_i + year_t + \varepsilon_{it} \tag{2}$$

where i indexes cities, t indexes time; $crime\_theft_{it}$ denotes the crime rate of theft in city i at time t; *index* denotes the digital finance inclusion index, $Post$ is a dummy variable that equals one for year 2018 onward and zero otherwise. μ_i and $year_t$ are city and year fixed effects, respectively. $X_{i,t-1}$ are control variables, and ε_{it} is the error term. We cluster standard errors at the city level. The interaction term $index_i \times Post$ captures the impact of the release of the “Specification” on the crime rate of theft in terms of impact intensity. The results in column (1) of Table 5 reveal a significant negative coefficient at the 1% level. This indicates that the development of mobile payments, marked by the release of the "Specification", has effectively reduced the crime rate of theft. Furthermore, the effect becomes more pronounced with the advancement of digital financial inclusion. These conclusions align with our previous findings.

3.3.2 Reconstruct Treatment and Control Groups

In our baseline analysis, we categorized cities in our sample into treatment and control groups using the median value of the digital financial inclusion index for each city in the year preceding the release of the "Specification". To verify the robustness of our findings, we've explored an alternative approach for constructing these groups. This alternative method involves dividing the sample cities into quartiles based on their digital financial inclusion index in the year before the release of the "Specification". In this approach, we designate the cities in the top 25% as the treatment group, while those below the top 25% make up the control group. Consequently, we introduce a new treatment group dummy variable, *Treat_re*, to test this approach.

The results in column (2) of Table 5 show that the estimated coefficient of *Treat_re*×*Post* is -0.4022, which is significant at the 1% level. These findings indicate that our results remain robust when we consider different thresholds for selecting the control group.

Table 5 Robustness Tests

Variable	(1) Continuous treatment	(2) Reconstruct treatment and control groups	(3) Exclude Samples in 2017	(4) Placebo Test
	Crime of theft			
index×Post	-0.0090*** (0.0022)			
Treat_re×Post		-0.4022*** (0.0890)		
Treat1×Post			-0.2104*** (0.0572)	
Treat2×Post2				0.0478 (0.0500)
Control Variables	YES	YES	YES	YES
City fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
R^2	0.2069	0.2040	0.1300	0.0891
N	1390	1390	1112	556

Furthermore, we anticipate that these additional empirical test results will exhibit a "dose effect". As the gap between the treatment and control groups in the development of digital financial inclusion widens, the estimated impact of mobile payments expansion on the reduction in the crime rate should increase. According to the results presented in column (2) of Table 5, the absolute value of the estimated coefficient of *Treat_re*×*Post* is greater than the absolute value of the estimated coefficient of *Treat*×*Post* in Table 3. This indicates that the estimated impact on the crime of theft rate in the top 25% cities is even pronounced than our baseline result, underscoring the robustness and strength of our findings.

3.3.3 Excluding Samples in the Year of Policy Change

Since the "Specification" was released in August 2016, the data in 2017 is mixed with prior and post treatment effects.[1] We can remove the sample observations in 2017, and set a new the dummy variable, *Treat1*, for the treatment group. The result in column (3) of Table 5 show that *Treat1*×*Post* is significantly negative at the 1% level. Our primary conclusion still holds.

3.3.4 Placebo Test

In this section, we conducted further verification to confirm that the policy change in 2016 was indeed a pivotal event with lasting impact. This analysis also serves to ensure that our results are not driven by our choice of sample period. To achieve this, we artificially designated a hypothetical time point, which is one period earlier than the actual release of the "Specification". We subsequently select a sample period that precedes this contrived shock, covering the years 2015 to 2016. Using the median of the digital financial inclusion index of each sample city in 2015, we reconstruct the treatment and control groups. Cities with an index value above the median are assigned to the treatment group, while cities below the median form the control group. *Treat2* represents this new treatment group. A new dummy variable, *Post2*, represents the counterfactual treatment period, which takes the value 0 in 2015, and takes the value 1 in 2016. If the estimated coefficient of the dummy variable *Treat2*×*Post2* is significant, meaning that the observed impact was attributable to other policies.

[1] The policy shock in 2016 is aligned with crime data from 2017.

The estimation results in column (4) of Table 5 reveal that the coefficient of *Treat2×Post2* is not statistically significant. This outcome contradicts the findings of our regression analysis in equation (1), indicating that the reduction in the theft crime rate cannot be attributed to other policy changes before the release of the "Specification." Thus, our baseline results from equation (1) are robust.

3.3.5 Lagged Control Variables

The verdict documents are organized by trial time instead of the time when the crime occurred. Since the trial usually takes about 6 to 12 months on average, in the baseline regression, we match crime data with lagged control variables.

In this section, we use the 2015-2019 control variable data without a lag period to match the theft crime rate data, and replace *Treat×Post* in the baseline DID model with the interaction term between *Treat* and the year dummy variable, to explore the impacts of mobile payments expansion on the theft rate.

The coefficient of the interaction term *Treat×Post* is significantly negative at the 1% level in column (1) of Table 6. This result suggests that the development of mobile payments significantly reduce the crime rate of theft in the treatment group. The results presented in the column (2) of Table 6 indicate that the interaction terms *Treat×year2016* and *Treat×year2017* are not significantly different from 0, meaning that there was no significant difference in the theft crime rate between the two groups of cities before the release of the "Specification," confirming that the parallelism assumption of the DID is met. Meanwhile, the coefficients of interaction term with the post-event year dummy variable, *Treat×year2018* and *Treat×year2019*, are significantly negative at the 1% level and the magnitude of these estimated coefficients gradually increase, indicating that the release of the "Specification" can significantly reduce the crime rate of theft in the treatment group cities and this effect has been increasing over time. These findings are consistent with the results matching crime data with lagged control variables.

Table 6 The effect of the development of mobile payments on the theft.

Variable	（1）	（2）
	Crime Rate of Theft	
Treat×Post	-0.2163***	
	(0.0497)	
Treat×year2016		0.0256
		(0.0510)
Treat×year2017		-0.0316
		(0.0554)
Treat×year2018		-0.1957***
		(0.0654)
Treat×year2019		-0.2446***
		(0.0692)
Control Variables	YES	YES
City fixed effects	YES	YES
Year fixed effects	YES	YES
R^2	0.1744	0.1757
N	1390	1390

4. Potential Mechanisms

4.1 Impact of Mobile Payments on Non-economic Crimes

Mobile payments expansion should have no impact on crimes that are not directly related to cash acquisition if it reduces theft rates by replacing cash in circulation. Thus, by examining the impact of mobile payments on the crime rate of non-economic crimes, it indirectly validates the mechanism from the expansion of mobile payments to the reduction of theft. Besides, one potential concern is that our findings may be influenced by another policy that took place in 2016, which could have affected crime rates. For instance, this could include an unknown anti-crime campaign or a sudden deployment or upgrade of the public surveillance camera system, especially in cities with prior better digital finance development. To address this issue, we replace the dependent variable of model (1) from theft crime to rape and murder to explore whether other types of crime were affected.[1]

The results, as presented in columns (1) and (2) of Table 7 for rape and columns (3) and (4) of Table 7 for murder, align with our hypothesis, as we found no significant relationships between access to mobile payments expansion and the rate of rape or murder.

These results highlight two crucial points. First, they eliminate the possibility of other policies counteracting crime as the driving force behind our findings. Second, our empirical results strongly suggest that mobile payments primarily influence crime through economic channels, given their lack of impact on non-economic crimes like rape and murder.

Table 7 The results on rape and murder.

	(1)	(2)	(3)	(4)
	Crime of rape		Crime of murder	
Treat×Post	-0.0021	0.0058	0.0015	0.0017
	(0.0047)	(0.0050)	(0.0029)	(0.0033)

[1] The retrieval process of the rape case and murder case data in this paper can be found in the Table B of appendix.

Control Variables	NO	YES	NO	YES
City fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
R^2	0.4939	0.5078	0.0501	0.0525
N	1080	1080	1125	1125

4.2 Mobile Payments and Household Cash Holdings

Criminologists have long recognized that cash transactions, due to their liquidity and transactional anonymity, tend to be associated with predatory crimes. Therefore, the recent surge in digital payment methods is expected to reduce the amount of physical cash in circulation, potentially leading to a decrease in street crimes (Wright et al., 2017; Pridemore et al., 2018). However, there exists a dearth of empirical evidence directly linking mobile payments to changes in cash holdings.

To bridge this gap, we leverage data from the 2015 and 2017 China Household Finance Survey (CHFS) to examine this relationship. Within the survey, participants provided information about the amount of cash held by their households.[1] This data allows us to establish a per capita metric for household cash holdings (referred to as "cash"), calculated by dividing total household cash holdings by the household size. By matching the payment usage index with CHFS data using city codes, we construct a panel dataset spanning 2015 to 2017 to conduct an empirical analysis at the household level. We consider the following model:

$$avecash_{jit} = \alpha + \beta_1 Payment_{it} + \beta_2 Z_{jit} + \beta_3 X_{it} + \mu_j + year_t + \varepsilon_{jit} \qquad (3)$$

where j denotes household, i denotes city, t denotes time, $avecash_{jit}$ denotes household

[1] The data obtained from the question “How much cash does your household currently hold” in the CHFS 2015 and 2017 questionnaires.

cash holdings per capita. $Payment_{it}$ denotes the payment usage index. Z_{jit} represents control variables on household level, including head of household characteristic variables (gender, age, education level, marital status, risk attitude[1]) and household characteristic variables (household income, elder people share, children share), X_{it} represents control variables on city level. μ_j and $year_t$ are household and year fixed effects respectively and ε_{jit} is the error term. The standard errors of the regression are clustered at the city level.

Table 8 The impact of mobile payments on per capita cash holdings of households.

	Cash holding
Payment	-0.0057**
	(0.0027)
Control Variables	YES
City fixed effects	YES
Year fixed effects	YES
N	18840
R^2	0.0166

Table 8 presents the impact of mobile payments expansion on per capita household cash holdings. After controlling for household-level and city-level characteristics, we find that the estimated coefficient of the payment usage index is -0.0057, which is significant at the 5% level. This implies that the adoption of mobile payments is associated with a substantial reduction in household cash holdings. To put it in practical terms, each standard deviation increase in the payment usage index leads to a decrease

[1] The question regarding risk attitude in the survey: If you have a choice, what kind of investment will you make? 1. High risk and high return projects; 2. Secondary high-risk and secondary high-return projects; 3. Average risk and average return projects; 4. Secondary low-risk and secondary low-return projects; 5. Unwilling to take any risks. This paper defines option 3 as risk neutral, while option 1 and option 2 are defined as risk preference, and option 4 and option 5 are defined as risk aversion.

of approximately 2782 yuan in per capita cash holdings among residents.[1]

4.3 DDD Estimation

To empirically investigate the direct relationship between mobile payments adoption, cash holdings, and theft crime rate, we construct the per capita household cash holdings at the city level, denoted as "avecash_city," using the cash holdings per capita at the household level within each city from CHFS 2015 and 2017. We then merge this data with theft crime rates and control variables using city codes. The sample size decreases to 149 prefectures due to the limited coverage of CHFS data at the city level. We consider a triple difference (DDD) model with cash holdings:

$$crime\_theft_{it} = \alpha + \beta_1 Treat \times Post \times avecash\_city_{i,t-1} + \beta_2 Post \times avecash\_city_{i,t-1} \\ + \beta_3 Treat \times avecash\_city_{i,t-1} + \beta_4 Treat \times Post + \gamma X_{i,t-1} + \mu_i + year_t + \varepsilon_{it} \tag{4}$$

where *i* indexes cities, *t* indexes time; $crime\_theft_{it}$ denotes the crime rate of theft in city *i* at time *t*; μ_i and $year_t$ are city and year fixed effects, respectively; $Post$ is a dummy variable that equals one for year 2018 onward and zero otherwise. $Treat$ is a dummy variable that equals one if the city belongs to the treatment group and zero if it belongs to the control group. ave*cash_city* represents the per capita cash holdings of households at the city level. $X_{i,t-1}$ are control variables, and ε_{it} is the error term. We cluster standard errors at the city level.

Since our dataset for model (4) is restricted to 149 prefectures, we first report our estimation results of model (1) for this subset of cities. In Table 9, columns (1) and (2) display these results. They reveal that within the subset of cities covered by CHFS data,

[1] The standard deviation of payment usage index is 48.81. Because the unit of household cash holdings per capita is 10,000 yuan, we calculate this value by 48.81×0.0057×10000=2782.17.

after accounting for fixed effects, the estimated coefficient of *Treat×Post* is -0.2108, which is statistical significance at the 5% level. After adding control variables, the estimated coefficient of *Treat×Post* negative and significant at the 10% level. These findings suggest that the expansion of mobile payments significantly reduces theft crime rates in the treatment group compared to the control group, specifically within the cities sampled by CHFS data. Notably, the estimated coefficient is larger than the baseline regression results presented in Table 3.

We then proceed to estimate the coefficients of *Treat×Post×cash_city*, reported in column (3) and column (4) of table 9. These results show that the interaction term's estimated coefficient is not only negative but also significant at the 5% level. These findings indicate that the expansion of mobile payments has a more pronounced effect in reducing theft crime rates in areas where households have a greater dependence on cash.

Table 9 Estimated results based on microdata sample cities and DDD method.

	(1)	(2)	(3)	(4)
	Crime of theft			
Treat×Post	-0.2108**	-0.1646*		
	(0.0872)	(0.0874)		
Treat×Post×cash_city			-1.6063**	-1.6876**
			(0.6401)	(0.7951)
Control Variables	NO	YES	NO	YES
City fixed effects	YES	YES	YES	YES
Year fixed effects	YES	YES	YES	YES
R^2	0.0925	0.1948	0.2315	0.2990
N	296	296	296	296

5. Concluding Remarks

Our research provides significant evidence demonstrating that the recent proliferation of mobile payments systems has had a substantial and consistent negative impact on theft, a common crime in China. And we provide empirical validation for the idea that mobile payments not only serve as a cash substitute in transactions but also lead to reduced household cash holdings. These results remain robust, unaffected by our empirical approach, city group categorization, or the exclusion of potential confounding factors. Nevertheless, we do not find any significant impact on non-economic crimes, such as rape and murder. These findings unveils that the expansion of mobile payments systems, driven by the introduction of the "Specification," mitigates theft by reducing the circulation of physical cash.

While our study draws from Chinese data, its implications reach far beyond national boundaries. Taking advantage of the latest advances in digital technology, payments via mobile phones have become increasingly popular worldwide, a trend further accelerated by the COVID-19 pandemic. Notably, even in economically challenged regions like Africa, there has been a remarkable upsurge in mobile payments adoption. According to data from the Global System for Mobile Communications Association (GSMA), the number of monthly active mobile payments accounts in Africa exceeded 160 million in 2020, marking an 18% increase compared to the previous year. Developing countries, where traditional financial services are less developed and relatively expensive, stand to benefit greatly from these advancements. The findings presented in our paper imply that the expansion of mobile payments systems has the potential to significantly enhance personal security in these regions, leading to substantial improvements in living standards. Thus, it has important implications for crime governance and economic development around the world.

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Appendix

Table A The complete list of cities in our sample.

Province	City
Beijing	Beijing
Tianjin	Tianjin
Hebei	Baoding, Tangshan, Langfang, Zhangjiakou, Chengde, Cangzhou, Shijiazhuang, Qinhuangdao, Hengshui, Xingtai, Handan
Shanxi	Linfen, Luliang, Datong, Taiyuan, Xinzhou, Jinzhong, Jincheng, Shuozhou, Yuncheng, Changzhi, Yangquan
Inner Mongolia	Ulanqab, Wuhai, Baotou, Hulunbuir, Bayannur, Chifeng, Tongliao, Ordos
Liaoning	Dandong, Dalian, Fushun, Chaoyang, Benxi, Shenyang, Panjin, Yingkou, Huludao, Liaoyang, Tieling, Jinzhou, Fuxin, Anshan
Jilin	Jilin, Siping, Songyuan, Baicheng, Baishan, Liaoyuan, Tonghua, Changchun
Heilongjiang	Qitaihe, Yichun, Jiamusi, Shuangyashan, Harbin, Daqing, Mudanjiang, Suihua, Jixi, Hegang, Heihe, Qiqihar
Shanghai	Shanghai
Jiangsu	Nanjing, Suqian, Xuzhou, Yangzhou, Wuxi, Taizhou, Huaian, Lianyungang, Zhenjiang
Zhejiang	Lishui, Taizhou, Jiaxing, Ningbo, Hangzhou, Wenzhou, Huzhou, Shaoxing, Zhoushan, Quzhou, Jinhua
Anhui	Bozhou, Lu'an, Hefei, Anqing, Xuancheng, Suzhou, Chizhou, Huaibei, Huainan, Chuzhou, Wuhu, Bengbu, Tongling, Fuyang, Maanshan, Huangshan
Fujian	Sanming, Nanping, Xiamen, Ningde, Quanzhou, Zhangzhou, Fuzhou, Putian, Longyan
Jiangxi	Shangrao, Jiujiang, Nanchang, Ji'an, Yichun, Fuzhou, Xinyu, Jingdezhen, Pingxiang, Ganzhou, Yingtan

Shandong	Dongying, Linyi, Weihai, Dezhou, Rizhao, Zaozhuang, Taian, Ji'nan, Zibo, Binzhou, Weifang, Yantai, Liaocheng, Heze, Qingdao
Henan	Sanmenxia, Xinyang, Nanyang, Zhoukou, Shangqiu, Anyang, Pingdingshan, Kaifeng, Xinxiang, Luoyang, Luohe, Puyang, Jiaozuo, Xuchang, Zhengzhou, Zhumadian, Hebi
Hubei	Shiyan, Xianning, Xiaogan, Yichang, Wuhan, Jingzhou, Jingmen, Xiangyang, Ezhou, Suizhou, Huanggang, Huangshi
Hunan	Loudi, Yueyang, Changde, Zhangjiajie, Huaihua, Zhuzhou, Yongzhou, Xiangtan, Yiyang, Hengyang, Shaoyang, Chenzhou, Changsha
Guangdong	Dongguan, Yunfu, Foshan, Guangzhou, Jieyang, Meizhou, Shantou, Shanwei, Jiangmen, Heyuan, Shenzhen, Qingyuan, Zhanjiang, Chaozhou, Zhuhai, Zhaoqing, Maoming, Yangjiang, Shaoguan
Guangxi	Beihai, Nanning, Chongzuo, Laibin, Liuzhou, Guilin, Wuzhou, Hechi, Yulin, Baise, Guigang, Hezhou, Qinzhou, Fangchenggang
Hainan	Sanya, Haikou
Chongqing	Chongqing
Sichuan	Leshan, Neijiang, Nanchong, Yibin, Bazhong, Guangyuan, Guang'an, Deyang, Chengdu, Panzhihua, Luzhou, Meishan, Mianyang, Zigong, Ziyang, Dazhou, Suining, Ya'an
Guizhou	Liupanshui, Anshun, Bijie, Guiyang, Tongren
Yunnan	Lincang, Lijiang, Baoshan, Kunming, Zhaotong, Puer, Qujing, Yuxi
Shaanxi	Xianyang, Shangluo, Ankang, Baoji, Yan'an, Yulin, Hanzhong, Weinan, Xi'an, Tongchuan
Gansu	Lanzhou, Jiayuguan, Tianshui, Dingxi, Pingliang, Qingyang, Zhangye, Wuwei, Baiyin, Jiuquan, Jinchang, Longnan
Qinghai	Xining
Ningxia	Zhongwei, Wuzhong, Guyuan, Shizuishan
Xinjiang	Urumqi, Karamay

Table B The retrieval process of crime case data.

Theft	The retrieval process of the theft case data in this paper is as follows: select advanced retrieval on the China Judgements Online, set "criminal case" as the case type, choose the document type as "verdict", and select "criminal cause of action” as “crime of property infringement-crime of theft", the trial procedure selects "criminal first instance", and the time span is "January 1, 2015 to December 31, 2019".

Rape	The retrieval process of the rape case data in this paper is as follows: select advanced retrieval on the China Judgements Online, set "criminal case" as the case type, choose the document type as "verdict", and select "criminal cause of action" as "crime of citizens' personal rights and democratic rights infringement-crime of rape", the trial procedure selects "criminal first instance", and the time span is "January 1, 2015 to December 31, 2019".
Murder	The retrieval process of the murder case data in this paper is as follows: select advanced retrieval on the China Judgements Online, set "criminal case" as the case type, choose the document type as "verdict", and select "criminal cause of action" as crime of citizens' personal rights and democratic rights infringement-crime of murder", the trial procedure selects "criminal first instance", and the time span is "January 1, 2015 to December 31, 2019".