

Jiang, Hongze; Liang, Pinghan

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Less cash, less theft? Evidence from fintech development in the People's Republic of China

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LESS CASH, LESS THEFT? EVIDENCE FROM FINTECH DEVELOPMENT IN THE PEOPLE'S REPUBLIC OF CHINA

Hongze Jiang and Pinghan Liang

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Hongze Jiang is a PhD student at the School of Government of Sun Yat-sen University, Guangzhou, People's Republic of China (PRC). Pinghan Liang is a professor at the Center for Chinese Public Administration Research/School of Government of Sun Yat-sen University, Guangzhou, PRC.

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Please contact the authors for information about this paper.

Email: liangph5@mail.sysu.edu.cn

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Asian Development Bank Institute
Kasumigaseki Building, 8th Floor
3-2-5 Kasumigaseki, Chiyoda-ku
Tokyo 100-6008, Japan

Tel: +81-3-3593-5500
Fax: +81-3-3593-5571
URL: www.adbi.org
E-mail: info@adbi.org

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Abstract

This research investigates the impact of Fintech development on an important type of crime: theft. Based on Becker's rational criminal theory, we suggest that Fintech development could mitigate theft activities by increasing the earnings from legitimate work, relaxing potential criminals' financial constraints, and reducing the expected gains from theft. We established a unique dataset containing information on more than 1 million theft defendants during the period 2014–18, which we extracted from 874,000 judgment statements. Then, we aggregated them to construct a city-year panel of theft activities and matched it with the city-level economic activities and Fintech development level. The results show that a 1 standard deviation increase in the Fintech development level has a significant association with a 0.39 standard deviation decrease in thefts' density. Robustness checks and instrumental variable estimation support the main results. Further, the development of Fintech reduces thefts' density by reducing residents' cash holding and providing more job opportunities. Finally, we utilized a nationally representative household survey to estimate the cost of theft for households, finding that victims suffer from more mental health problems, increasing their health expenditure. Our results suggest an unexpected source of welfare gain from the development of Fintech: an improvement in public security.

Keywords: fintech, theft, crime, People's Republic of China

JEL Classification: G59, K14, K42, C81

Contents

1.	INTRODUCTION	1
2.	LITERATURE AND THEORETICAL FRAMEWORK	2
2.1	Literature Review.....	2
2.2	Theoretical Framework	3
3.	DATA	4
4.	RESULTS.....	7
4.1	Baseline Results.....	7
4.2	Robustness Check.....	9
4.3	IV Results.....	10
4.4	Heterogeneity Analysis	10
5.	MECHANISM ANALYSIS	12
6.	THE HEALTH COST OF THEFT ACTIVITIES.....	14
7.	CONCLUSION.....	16
	REFERENCES	18

1. INTRODUCTION

This paper examines the relationship between Fintech development and theft activities. Theft is an important and frequent type of criminal activity worldwide, causing considerable cost to the society. A study in the US showed that, including the victim costs, criminal justice system costs, crime career costs, and intangible costs, the total per-offense cost for theft (larceny, motor vehicle theft, and household burglary) ranges from \$3,532 to \$10,772 in 2008 USD (McCollister, French, and Fang 2010). In Chicago, during the period 2001–12, larceny, burglary, and theft auto represented 89% of all 1.8 million property crimes (Herrnstadt et al. 2021). In the People's Republic of China (PRC), theft accounted for 64%–71% of all criminal cases that the police filed between 1995 and 2010 (Chen and Liu 2013). Moreover, theft easily turns into other crime types that involve violence or the threat of violence, such as robbery, leading to even greater harm to the victims (Miller, Cohen, and Rossman 1993; McCollister, French, and Fang 2010).

By definition, theft targets property and cash, so the way in which citizens use and hold cash in daily life affects the expected gains from theft activities. The PRC has witnessed the rapid development of Fintech, featuring the wide spread of mobile transfer and payment systems, in the past decade and has become a world leader in the adoption of Fintech services. This substantially reduces the need to hold cash for daily transactions, making theft less profitable for a rational decision maker who trades off the expected gains from theft against the opportunity cost. Hence, the PRC provides us with an ideal context in which to examine the impact of Fintech development on theft activities.

Based on the rational criminal model à la Becker (1968), first, we analyzed the impact of Fintech on theft activities. The indications are that Fintech could contribute to decreasing theft by reducing its expected gains, relaxing financial constraints, and increasing the expected earnings from legitimate work. Then, we proposed our hypotheses.

To test the hypotheses, we employed administrative data to construct a city-level measure of theft activities. We scraped all publicly available judgment statements on theft in the PRC during the period 2014–18 and used text recognition techniques to extract the key information about the defendants, courts, and cases. To the best of our knowledge, this is the most comprehensive nationwide measure of theft activities at the city level. Then, we matched this information with city-level economic activities, demographic structure, Fintech level, and government efforts to control crime to construct city-year paired panel data. The empirical analysis indicated that a 1 standard deviation increase in the Fintech level has a significant association with a 0.39 standard deviation decrease in theft activities. Various robustness checks supported our main results. To deal with the potential omitted variable problem, we interacted the geographic distance from the city to Hangzhou, the headquarters of Alipay (the leading Fintech service provider), with the national level of Fintech development as the instrumental variable for the regional Fintech level. The mechanism analysis showed that Fintech development reduces theft by facilitating mobile payments and activating the local economy. However, we found no evidence that Fintech works by releasing financial constraints. Finally, utilizing a nationally representative household dataset, we showed that theft incurs substantial mental health problems for victims and increases their medical expenditure. This suggests the large unexpected social benefits of Fintech development.

The organization of the rest of this paper is as follows: Section 2 reviews the literature and lays out the theoretical framework as well as the empirical hypotheses; Section 3 describes the data; Section 4 presents the empirical results; Section 5 examines the mechanism; Section 6 discusses the social cost of theft from the perspective of mental health; and Section 7 concludes.

2. LITERATURE AND THEORETICAL FRAMEWORK

2.1 Literature Review

Fintech is the fusion of finance and technology, and the scope of Fintech activities ranges from mobile payments, money transfer, peer-to-peer loans, and crowdfunding to blockchain, cryptocurrencies, and robo-investing (Goldstein, Jiang, and Karolyi 2019). Fintech not only transfers the type of financial services, like the preceding ATMs and wire transfers, but also rapidly creates many more competitors outside the traditional sectors.

Previous research has documented the beneficial role of Fintech development in the expansion of credit (Buchak et al. 2018; Hau et al. 2019a), the increase in household consumption (Xie et al. 2018), and the promotion of entrepreneurship (Fu and Huang 2018; Zhang et al. 2020a). Studies have also extensively investigated the relationship between Fintech and traditional financial services, and many have suggested that Fintech leads to more competition with the traditional service providers rather than broadening access to finance (Buchak et al. 2018; Fuster et al. 2019; Tang 2019; Vallée and Zeng 2019).

Fintech is a wide area with an ever-expanding scope. We focused on the mobile payment side of Fintech. Starting with Baumol (1952), research has formally investigated the convenience of cash in transactions in economics. Lately, many studies have addressed the consumer choice between cash and non-cash payments and found that the share of cash use decreases with the transaction size (Borzekowski, Kiser, and Ahmed 2008; Ching and Hayashi 2010; Koulayev et al. 2016; Wang and Wolman 2016). This is due to the threshold of non-cash payments, such as the fixed per-transaction cost associated with credit cards, debit cards, and so on. On the other hand, no per-transaction cost arises from mobile payment as people use mobile money accounts to transfer money. Hence, as long as the Internet access is stable and there is wide use of mobile phones, there is no threshold for mobile payments, and mobile payments can substitute the use of cash even in small transactions. This has important implications for entrepreneurship growth and macroeconomic development (Beck et al. 2018; Huang and Huang 2018; Hau et al. 2019b; Zhang et al. 2020b).

This paper relates the development of Fintech to criminal activities. Both theory and empirical studies have suggested that most criminals transit between legitimate jobs and illegitimate work, leading to high elasticity of the crime supply (Becker 1968; Freeman 1999). Research has documented well that the law enforcement effort could deter criminal activities (Corman and Mocan 2000; Di Tella and Schargrodsky 2004). The list of general economic and social conditions that affect crimes is long, and some are specific to the PRC, including unemployment (Raphael and Winter-Ember 2001; Zhang et al., 2018), education (Deming 2011), pressure in the marriage market in the PRC (Edlund et al. 2013; Cameron, Meng, and Zhang 2019), demographic structure (İmrohoroglu, Merlo, and Rupert 2006; Zhang et al. 2014; Guo et al. 2020a), urban–rural migration (Chen, Li, and Chen 2009), urban–rural income inequality (Zhang, Liu, and Liu 2011), social insurance (Zhang, Du, and Xu 2019), air pollution (Herrnstadt et al. 2021), and so on. Moreover, the characteristics of victims make a

difference to criminals' choice of target, especially in fraud, such as their demographic characteristics (Lee and Soberon-Ferrer 1997; Ross, Grossmann, and Schryer 2014; Lichtenberg et al. 2016) and their credit constraints and financial access (Gao, Ma, and Xu 2020; Liang and Jiang 2020). The development of Fintech in the PRC is to a large extent an initiative of private companies, such as Alibaba and WeChat; hence, it has no direct relationship with the deterrence of crimes. However, it may affect both the opportunity cost and the expected gains underlying the decision to commit theft.

2.2 Theoretical Framework

We used the standard economic model of decision making (Becker 1968; Freeman 1999) to describe individuals' tradeoff between theft and legal activity. Equation (1) compares the expected utility from those acts.

$$(1 - p)U(W_c) - pU(S) > U(W) \quad (1)$$

in which W_c is the gain from successful theft, p is the probability of arrest, S is the extent of punishment once arrested, and W is the earnings from legitimate work. Hence, $pU(S) + U(W)$ represents the expected cost to criminals, including the opportunity cost, punishment cost, and psychological cost. The decision maker will choose to commit theft in a given time period when the expected gains from theft exceed the expected cost.

From this equation, we could derive three potential channels through which the Fintech level could mitigate theft activities. First, the diffusion of Fintech, especially the diffusion of mobile payment systems, directly reduces the gains from theft W_c . From equation (1), it is clear that the expected gains from successful theft have a positive relationship with the likelihood of theft. According to the PRC's criminal law, theft covers household burglary, larceny, theft of motor vehicles, and theft with weapons, and the statistics show that burglary and larceny account for the largest part (Zhang, Liu, and Liu 2011). Harbaugh, Mocar, and Visser (2013) provided experimental evidence that the probability of theft increases with the amount of money that it is possible to steal. Beck et al. (2018) used a general equilibrium model to show that mobile payments could reduce the probability of theft. The use of mobile payments through smartphones considerably reduces the need to hold cash in daily life and hence the money that is available to steal. Even though thefts could target smartphones, it is not easy for traditional burglars to steal the money in electronic accounts since the owners can easily lock their smartphone remotely. This considerably reduces the need to hold cash in daily life, either in public or at home.

Second, the mitigating effect of Fintech varies with the local financial development level. Equation (1) implies that the risks and the attitudes toward risks influence the decision to commit theft. Previous research has shown that those individuals with a low risk aversion level or a lack of self-control and emotion control ability are more likely to steal (Arneklev et al. 1993; Zhang et al. 2014). One implication is that low-risk-averse individuals are more likely to make risky decisions when they face adverse shocks in daily life. The development of Fintech expands the access to credit and relaxes the financial constraints. Consequently, it is easier for individuals to smooth their consumption. Hence, the mitigating effect of Fintech is more salient in previously less financially developed areas as the financial constraints in these areas were more binding.

Third, the mitigating effect of Fintech on theft depends on the local economy. It is noteworthy that many new service industries have arisen following the development of Fintech in the PRC. On the one hand, some new industries have substantially reduced the gains to theft; for instance, the emerging shared bikes (Mobile Bike) diminish the need to purchase private bicycles and consequently the valuable objects to steal. On the other hand, many new industries are labor intensive and create more job opportunities for low-skilled labor in urban areas, such as e-commerce (Alibaba), food delivery (Meituan), ride hailing (DiDi), and package delivery (SF express). Furthermore, the mobile transfer and payment system based on Alipay and WeChat reduces the market entry barriers and encourages entrepreneurship as commerce can operate without cash or credit card transactions and individuals can run a business without huge investment, such as live streaming on a short-form video platform (TikTok). Equation (1) also indicates that the earnings from legitimate jobs are the key to the decision to commit theft. In general, in the PRC, thieves are from younger cohorts with lower educational attainment (Zhang et al. 2014). Hence, they are low-skilled workers in the labor market, with fewer available job opportunities. However, the success of these new industries also depends on the local economy as scale of economy characterizes many of them. Hence, Fintech is more likely to activate developed regions and lead to a beneficial mitigating effect on theft.

Hence, we proposed the following hypotheses for empirical examination:

H1: The development of Fintech reduces theft activities.

H2: The development of Fintech mitigates theft activities by facilitating mobile transfers and payments and reducing cash holding.

H3: The mitigating effect of Fintech on theft is larger in the less financially developed areas.

H4: The mitigating effect of Fintech on theft is larger in the regions with higher per capita income and a lower unemployment rate.

3. DATA

For this research, we constructed panel data covering four province-level municipalities (Beijing, Shanghai, Tianjing, and Chongqing) and all 285 prefecture-level cities in the PRC during the period 2014–18. We extracted the data on city-level economic activities and the demographic structure from the statistical annuals of Chinese cities.

We constructed the measure of Fintech development at Peking University under the name Peking University Digital Financial Inclusion Index of China, releasing it in 2020 (Guo et al. 2020a). The construction of this annual index took place in cooperation with Alipay, a leading mobile payment service provider in the PRC. This index covers approximately 2800 counties, 337 cities (municipal, prefecture, and county level), and 31 provinces over the period 2011–18. It consists of three sub-indices—coverage, depth of use, and extent of digitalization—and 33 variables. In general, the coverage index aggregates the number of Alipay accounts, the number of bank cards associated with an Alipay account, and so on, at the regional level. The depth index measures the use of digital finance services, including payments, mutual funds, loans, insurance, investment, and credit. The digitalization index considers the facilitation of payments, cost, and so on; in particular, it includes the size of mobile payments and the share of QR codes in the payment process. Guo et al. (2020a) presented the details of the index construction. In 2018, Hangzhou, Shanghai, Shenzhen, Nanjing, and Beijing

were the top five cities in the level of Fintech development, while Haidong, Yushu, Shigatse, Linxia, and Huangnan recorded the lowest Fintech development levels.

We constructed a measure of theft activities covering 289 prefecture-level cities and above over the period 2014–18 from the publicly available judgment statements on China Judgements Online (<https://wenshu.court.gov.cn/>). The Supreme People's Court of the People's Republic of China runs this website, having launched it officially on 1 July 2013. Now, the courts at all levels in the PRC upload their judgments, verdicts, and conciliation statements to this website; hence, this website provides full coverage of courts in the PRC, case types, and presiding judges. It has become the largest website for judgments, verdicts, and conciliation statements in the world. All judgments, verdicts, and conciliation statements now appear on the Internet, but the website conceals those involving State secrets or juvenile delinquency, cases closed through mediation or confirming the validity of mediation agreements, divorce litigation or cases involving the custody and guardianship of minors, and content involving personal privacy (Supreme People's Court 2017). Various researchers have conducted research on corruption, local protectionism, and the impact of air pollution using the judgment statements (Wang 2018; Kahn and Li 2020).

We scraped all judgments, verdicts, and conciliation statements related to theft of first instance.¹ We used the regular expressions to extract the key information about thefts—the demographic information, the date and location of the judgment, and the punishment that the offenders received—from these statements and matched the information on theft activities with the regional characteristics. Finally, we established a unique dataset containing information on 1,142,797 theft defendants during the period 2014–18 from 874,356 judgment statements. To the best of our knowledge, this is the first comprehensive dataset about theft activities at the city level in the PRC.

There are some caveats. First, measuring criminal behavior accurately in the real world is a worldwide challenge (Freeman 1999). If the gains from reporting crime are small, victims will not report theft to the police and consequently the crime will not reach the court. Second, according to the PRC's criminal law, theft cases reach the court only when the value of loss exceeds certain thresholds (which local courts have defined), and the police only impose administrative punishment on minor theft. Hence, there is a gap between the number of reported thefts and the number of theft judgment statements. However, in general, the unreported cases are relatively minor (Skogan 1977), so the official records are still a reliable measure of criminal activities (Levitt 1998). Moreover, we could not retrieve the exact criminal date for each defendant, as one defendant may have committed multiple theft actions, which cannot be recognized from the text. Hence, we aggregated the number of theft defendants according to the year when the court made the judgment. Since the evidence against a theft defendant is relatively clear, as the extremely low appeal and protest rates reflect, and the time length between the arrest and the judgment date is 2 or 3 months on average, based on a random sample from all the judgment statements, we think that the measurement error due to the missing date of theft actions is still acceptable. Since the regional economy and public security, which are region specific and relatively stable across the sample period, determine the thresholds of loss value for a theft judgment, we considered our sample of theft activities as censored data on all theft activities. We calculated the theft rate by dividing the number of theft defendants in a year over the total population of a city as the dependent variable. The unit is the number of theft

¹ According to this website, defendants only appealed or protested 0.53% of theft cases, a much lower figure than for other cases, for which the average share of appealed or protested cases is 28.17% (Liang and Jiang 2020).

defendants per 100,000 persons. Figures 1 and 2 illustrate the prefecture–city-level theft rate in 2014 and 2018, respectively. The darker the color of a city, the higher the number of theft defendants per 100,000 persons. As the figure shows, especially the cities in Zhejiang and Guangzhou, Shenzhen, experienced a decline in the theft rate.

Figure 1: Theft Rate in 2014

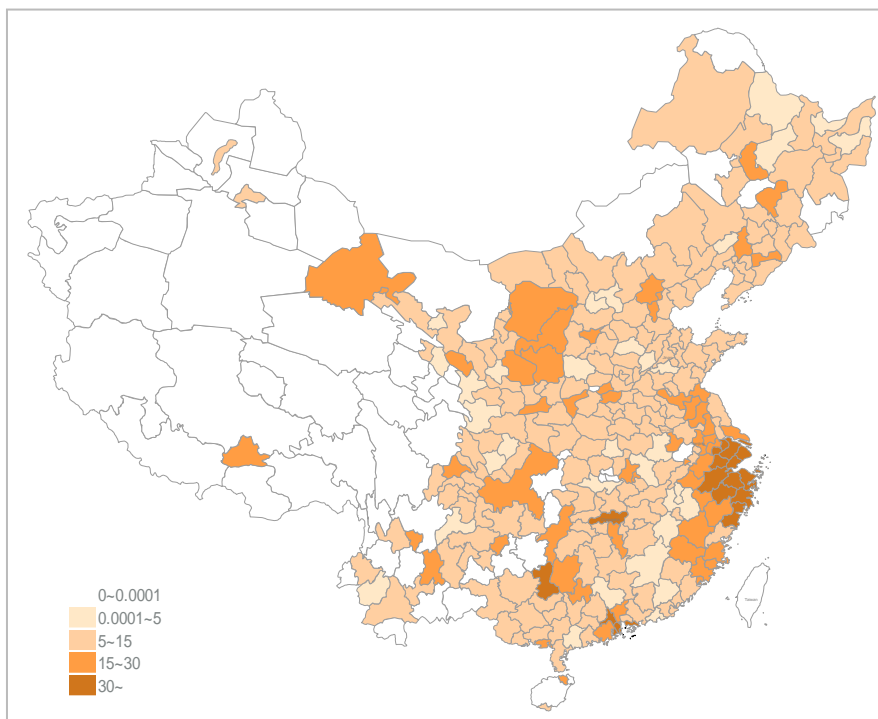
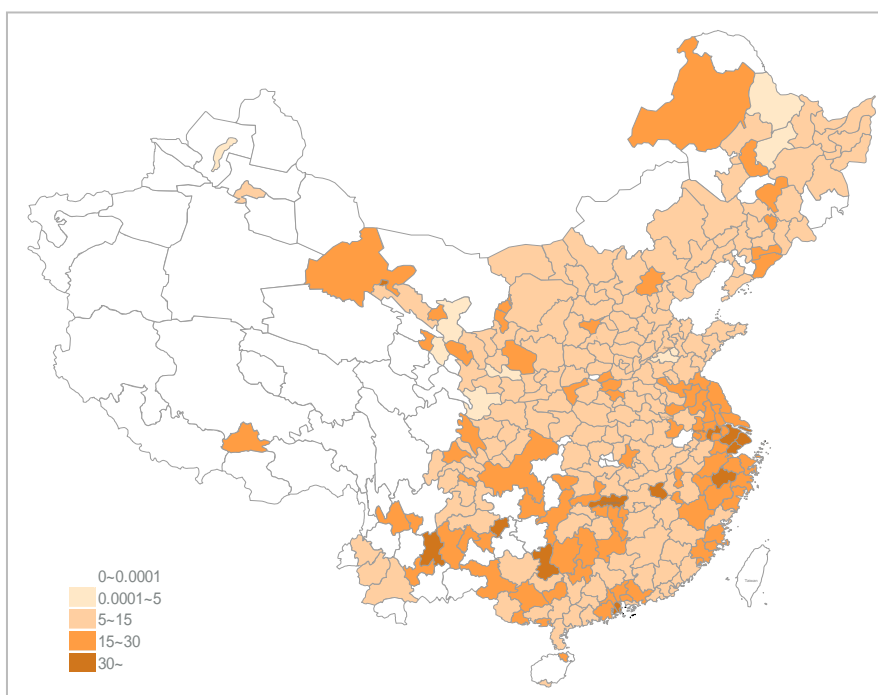


Figure 2: Theft Rate in 2018



In the regression, we also included the variables that may affect theft activities. We controlled for the regional economic activities (using the GDP per capita as a proxy), government enforcement effort (with the fiscal expenditure per capita as a proxy), feasibility of theft (using the population density as a proxy), financial development (the ratio of bank deposits and loans to the GDP), internet infrastructure level (mobile phones per capita and internet users per capita), education level (the number of students attending higher education institutions), the official unemployment rate, and the share of secondary industry workers in the total labor force.

Moreover, to avoid possible regional differences in uploading judgment statements, as well as the trend of criminal activities other than theft, we included the number of criminal judgment statements of first instance other than theft over the population. Furthermore, we took into account the impact of surveillance devices, which may arise with the development of internet infrastructure. We also scraped all procurement contracts of “video surveillance” during the period 2014–18 from Chinese Central Government Procurement (<http://www.ccgp.gov.cn/>), which the Ministry of Finance runs. We aggregated the number of contracts to the city level to measure the strength of the surveillance effort. Table 1 presents the descriptive statistics of all the variables.

Table 1: Descriptive Statistics

Variables	Unit	No. of Observations	Mean	Standard Deviation	Minimum	Maximum
Theft rate	Number of theft defendants per 100,000 persons	1,443	14.4943	9.5978	1.3686	73.2828
Fintech development		1,444	193.8537	37.4530	105.6100	302.9800
Coverage index		1,444	182.2481	35.6811	67.3800	290.3200
Depth index		1,444	188.4813	51.6018	71.0600	325.6800
Digitalization index		1,444	241.9452	43.7596	134.6500	581.2300
Log (GDP per capita)		1,443	10.7605	0.5322	9.2273	12.2807
Log (fiscal expenditure per capita)		1,443	9.1013	0.3746	8.0442	11.6669
Population density	Per km ²	1,443	469.5481	554.7243	5.7229	6,398.3281
Deposit&loan/GDP		1,444	2.5455	1.2554	0.7167	13.5303
Average mobile phones	Per capita	1,440	1.0197	0.3367	0.1217	3.1549
Average internet users	Per capita	1,434	0.2296	0.1317	0.0038	1.2620
Higher education students	Per 10,000 persons	1,409	178.2379	206.4927	2.4430	1,148.4382
Official unemployment rate		1,421	0.0514	0.0307	0.0005	0.2668
Share of secondary industry workers		1,443	0.4480	0.1448	0.0753	0.8343
Number of other criminal judgment statements	Per 100,000 persons	1,443	52.1220	24.9338	8.6545	318.4437
Video surveillance procurement posts		1,445	25.6007	50.7123	0	621

4. RESULTS

4.1 Baseline Results

We employed the following model (2) to analyze the impact of Fintech on theft activities:

$$Steal_Crime_{it} = \alpha + \beta IF_{it} + \gamma X_{it} + \mu_i + year_t + \varepsilon_{it} \quad (2)$$

$Steal_Crime_{it}$ is the number of theft defendants per 100,000 persons in city i in year t . IF_{it} is the core explanatory variable, the corresponding Fintech development level. X_{it} is a set of control variables, as Table 1 lists. $year_t$ captures the time fixed effect that affects all cities, like macroeconomic policies, economic cycles, and so on. μ_i captures the city-specific time-invariant unobservables, such as culture, geography, the threshold of loss value of theft to reach the court, and so on. The standard error, ε_{it} , is the robust standard error, clustered at the city level. To facilitate the interpretation and comparison of the coefficients, we standardized the digital financial inclusion index and the theft rate, respectively, for example each observation minus the mean, then divided them by the sample standard deviation.

Table 2: Baseline Results

Dependent Variable	(1) Theft Rate	(2) Theft Rate	(3) Theft Rate
Fintech development	-0.2988** (0.1197)	-0.3933*** (0.1168)	-0.3172*** (0.1112)
Log GDP per capita		0.6877*** (0.1977)	0.3903* (0.2056)
Log fiscal expenditure per capita		-0.1583 (0.1247)	-0.1295 (0.1183)
Population density		-0.0001 (0.0002)	-0.0002 (0.0002)
Deposit&loan/GDP		0.0809* (0.0445)	0.0814* (0.0478)
Average mobile phones		0.0550 (0.1448)	0.0714 (0.1448)
Average internet users		0.0797 (0.1550)	-0.0169 (0.1628)
Higher education students		0.0012** (0.0005)	0.0012** (0.0005)
Unemployment rate		-1.1852 (0.9898)	-0.9203 (0.8286)
Share of secondary industry workers		-0.0014 (0.0037)	-0.0032 (0.0036)
Number of criminal judgment statements		0.0071*** (0.0024)	0.0073*** (0.0023)
Video surveillance procurement posts		-0.0001 (0.0004)	-0.0001 (0.0004)
Year fixed effect	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes
Province-year fixed effect	No	No	Yes
Observations	1,442	1,383	1,383
R-squared	0.1817	0.2669	0.3028
No. of cities	289	286	286

Note: *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The parentheses contain the standard errors clustered at the city level.

Table 2 reports the OLS results from equation (2). Column (1) only controls for the city and year fixed effects. Column (2) delivers our preferred specification as equation (2) and controls for city-level variables; in addition, Column (3) adds the province-year fixed effect to capture the effect of province-specific, time-variant unobservables on theft activities. It turned out that the development of Fintech has a significant negative

association with the theft rate, which supports our H1. The coefficient in Column (2) indicates that, on average, a 1 standard deviation increase in the Fintech development level has a significant association with a 0.39 standard deviation decrease in the theft rate. In other words, the number of theft defendants per 100,000 persons reduces by 3.78, equal to 26% of the mean level. Hence, the development of Fintech substantially mitigates theft activities.

Among the control variables, the log GDP per capita, deposit&loan/GDP, and higher education students have a significant correlation with a higher theft rate, indicating that thieves also target valuable objects. The average numbers of mobile phones and internet users are not significant, indicating that Fintech works independently from the development of internet infrastructure. Moreover, neither the fiscal expenditure per capita nor the number of video surveillance procurement posts is significant, but the number of other criminal judgment statements is positively significant, suggesting a close relationship between theft and other types of crimes.

4.2 Robustness Check

Table 4 conducts a series of robustness checks. Column (1) excludes the theft rate in four municipal cities (Beijing, Shanghai, Tianjin, and Chongqing) as these cities may receive more political attention and pressure and have higher public security efforts. The impact of Fintech is still robust, and the magnitude is close to the results in Column (2), Table 2.

Column (2) excludes the judgment statements that the railway transportation courts have released. In the PRC, there are 37 railway courts, which have judicial control over all cases occurring on trains and at train stations. These courts do not belong to any cities, and their jurisdiction is larger than any single city. We excluded the defendants in these statements and recalculated the theft rate. Column (3) shows that the estimated coefficient is almost identical to the results in Table 2.

In Column (3), we further examined the impact of Fintech development on theft activities on trains separately. Many theft activities on trains and in train stations target travelers; hence, cash-holding behavior is more important for theft on trains. Since the number of travelers in each jurisdiction of a railway court is not available, we used the number of theft defendants as the dependent variable and the Fintech development in the location of a railway transportation court as the core explanatory variable. The city-level control variables also refer to the location city. It turned out that the Fintech development still significantly reduces theft activities on trains.

There are about 30,000 online unpublicized judgment statements. They may involve state secret or juvenile delinquency and so on; hence, the Supreme Court waives their publication. We only have the date and court of the judgment as well as the number of statements. In Column (4), we assigned one theft defendant to each unpublicized statement to calculate the regional theft rate, and the result is close to that in Table 2.

About 18% of judgment statements include more than one defendant. We considered them as group theft, in which the criminals' incentives are more complex (Freeman 1999). In Column (5), we excluded these statements to recalculate the theft rate for individual thieves. The result is still significant.

Table 3: Robustness Check

	(1)	(2)	(3)	(4)	(5)
	Exclude Municipal Cities	Exclude Railway Courts	Railway Transportation Courts	Unpublicized Statement	Exclude Group Theft
Dependent Variable	Theft Rate	Theft Rate	Theft No.	Theft Rate	Theft Rate
Fintech development	−0.4256*** (0.1134)	−0.3914*** (0.1170)	−1.2156* (0.6836)	−0.4263*** (0.1121)	−0.3169*** (0.1170)
Control variables	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes
Observations	1,363	1,383	180	1,383	1,383
R-squared	0.2758	0.2673	0.1398	0.2866	0.3169
No. of cities	282	286	37	286	286

Note: The control variables are the same as in Table 2. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The parentheses contain the standard errors clustered at the city level.

4.3 IV Results

It is possible that residents choose to adopt mobile payments in the expectation of avoiding the theft risk. Though our panel data structure controlled for time-specific and region-specific unobservables, it could not control for the city-specific time variation. Hence, we used an instrumental variable to deal with the endogeneity problem.

Following Fu and Huang (2018) and Zhang, Du, and Xu (2019), we used the geographic distance from the city to Hangzhou, the headquarters of Alibaba and Alipay, to construct the instrumental variable. According to Guo et al. (2020a), spatial factors affect the diffusion of Fintech: the further from Hangzhou, the more difficult the promotion of Alipay. Hence, the geographic distance satisfies the relevance condition. On the other hand, the geographic distance to Hangzhou is unlikely to correlate with the local theft risk or the law enforcement effort, hence satisfying the exclusion restriction. However, since the geographic distance to Hangzhou is time invariant, we interacted this distance with the national level of Fintech development in each year to construct our IV. Table 4 reports the results. Again, the results are significant, supporting our H1. It is noteworthy that the magnitude of the coefficient for Fintech development expands substantially, indicating that this distance may also represent some other factors. For instance, the expansion of e-commerce platforms, such as Alibaba, may also reduce the number of targets that are attractive to thieves.²

4.4 Heterogeneity Analysis

The mitigating effect of Fintech might relate to the value of theft cases. It is possible that the thieves are not frequent criminals when the value is smaller and that they undertake less cost–benefit analysis. We used the amount of penalties of each case as a proxy for the value of theft. Columns (1) and (2) show the median of penalties (3,000 RMB) to divide the sample. Then, we used equation (2) to run a regression on these two subsamples. It turned out that the mitigating effect of Fintech is only significant for theft activities with a large loss and is insignificant for minor theft actions.

² Many major delivery companies are located near Hangzhou, and the buyers in Zhejiang province (the capital is Hangzhou), Jiangsu province, and Shanghai usually enjoy free delivery services through Alibaba.

Table 4: IV Result

Dependent Variable	(1)	(2)
	Second Stage	First Stage
	Theft Rate	Fintech
Fintech development	–2.3197*** (0.4571)	
Instrumental variable		–0.0001*** (0.0000)
Control variables	Yes	Yes
Year fixed effect	Yes	Yes
City fixed effect	Yes	Yes
RKF value		66.87
Observations	1383	1383
R-squared	0.0533	
No. of cities	286	

Note: The instrumental variable is the multiplier of the geographic distance from the city to Hangzhou and the national level of Fintech development. The control variables are the same as in Table 2. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The parentheses contain the standard errors clustered at the city level.

In Columns (3)–(5), we divided the theft defendants according to their education level. Column (3) uses the number of theft defendants who received less than 6 years of education per 100,000 persons as the dependent variable. Column (4) uses the number of theft defendants who received 6 to 12 years of education per 100,000 persons as the dependent variable. Column (5) uses the number of theft defendants who received more than 12 years of education per 100,000 persons as the dependent variable. It is noteworthy that 88% of all the theft defendants in our sample received less than 12 years of education, that is, they did not finish high school. We ran OLS regression as equation (2) for these three subsamples. The results show that Fintech development has a similar mitigating effect for thieves with low and medium education levels, but the mitigating effect is the largest for those thieves with a relatively high education level. In other words, the development of Fintech increases the opportunity cost of theft action for highly educated individuals the most. Perhaps those highly educated individuals are more familiar with exploiting internet-complementary jobs. This is consistent with the finding that less-educated workers' employment gains have been lower in Africa since the introduction of the fast Internet (Hjort and Poulsen 2019).

We calculated the theft rate using the medium age of theft defendants (33 years) in Columns (6) and (7) and ran an OLS regression as equation (2) for these two subsamples. Fintech reduces the theft actions for all ages, but the mitigating effect of Fintech development is larger for relatively younger individuals, who are more adaptive to the development of Fintech and are more likely to take the new service jobs that the development of Fintech has created.

Table 5: Heterogeneity Analysis

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
	Large Loss Value Theft Cases	Small Loss Value Theft Cases	Theft Education ≤6 Years	6 Years <Theft Education ≤Years	Theft Education >12 Years	Theft Age ≤33 Years	Theft Age >33 Years
Dependent Variable	Theft Rate						
Fintech development	−0.3910*** (0.1245)	−0.1443 (0.0964)	−0.3065*** (0.0977)	−0.2914*** (0.1024)	−0.4970* (0.2612)	−0.3720*** (0.1148)	−0.2982*** (0.1051)
Control variable	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,383	1,383	1,383	1,383	1,281	1,373	1,378
R-squared	0.1706	0.1650	0.2300	0.2392	0.1269	0.2495	0.2468
No. of cities	286	286	286	286	264	284	285

Note: The control variables are the same as in Table 2. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The parentheses contain the standard errors clustered at the city level.

5. MECHANISM ANALYSIS

We first examined the heterogeneous impacts of different aspects of Fintech development. Table 6 considers the influence of the coverage index, depth index, and digitalization index, respectively. We used these three indices as the core explanatory variables and ran the regression as equation (2). It turned out that only the digitalization index, which measures the share of mobile payments, significantly reduces theft activities. This is consistent with our H2. The depth index has an insignificant correlation with theft activities. The coverage index, which measures the number of Alipay users and the number of bank cards associated with an account, even has a positive correlation with theft activities, though it is only significant at the 10% level. It might be due to this index having a high correlation with the number of mobile phone users, and mobile phones are a valuable target for theft activities. Moreover, it suggests that the relaxation of financial constraints is unlikely to be the reason for Fintech mitigating theft activities.

Table 6: The Heterogeneous Impact of Sub-indexes

	(1)	(2)	(3)
Dependent Variable	Theft Rate	Theft Rate	Theft Rate
Coverage index	0.3136* (0.1709)		
Depth index		0.0180 (0.1554)	
Digitalization index			−0.1398*** (0.0303)
Control variables	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes
Observations	1,383	1,383	1,383
R-squared	0.2606	0.2536	0.2873
Number of cities	286	286	286

Note: The control variables are the same as in Table 2. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The parentheses contain the standard errors clustered at the city level.

To test H2 further, we used a regular expression to identify the cash-related and mobile phone-related cases from the text of judgment statements. In Table 7, Column (1) calculates the theft defendants of cash-related cases per 100,000 persons as the dependent variable, and Column (2) uses the theft defendants of mobile phone-related cases per 100,000 persons as the dependent variable. The mitigating effect of Fintech on cash-related theft activities is larger and more significant. This further supports our H2.

Column (3) in Table 7 uses the deposit&loan/GDP to measure the regional financial development level. We added an interaction term between Fintech development and financial development in equation (2). The coefficient of the interaction term is insignificant, rejecting H3. Hence, Fintech does not work by expanding and substituting the access to credit.

Table 7: Mechanism Analysis (I)

	(1)	(2)	(3)
	Cash-Related	Mobile Phone -Related	
Dependent Variable	Theft Rate	Theft Rate	Theft Rate
Fintech development	-0.4059** (0.1893)	-0.3045* (0.1682)	-0.3971*** (0.1152)
Fintech development* financial development			0.0000 (0.0006)
Control variables	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes
Observations	1,383	1,383	1,386
R-squared	0.2381	0.5157	0.2670
No. of cities	286	286	286

Note: The control variables are the same as in Table 2. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The parentheses contain the standard errors clustered at the city level.

To test H4, we added the interaction term between the Fintech development and the log GDP per capita and the interaction term between the Fintech development and the unemployment rate, respectively, in equation (2). Columns (1) and (2) in Table 8 show the regression results. It turns out that the mitigating effect of Fintech is stronger when the GDP per capita is higher or the unemployment rate is lower, supporting our H4. Further, we used the median GDP per capita and the unemployment rate in 2014, respectively, to divide the cities into subsamples. Again, the results demonstrate that the mitigating effect of Fintech only appears in developed (high GDP) regions and low-unemployment regions, and the coefficient of Fintech is insignificant in underdeveloped (low GDP) and high-unemployment regions. The differences in coefficients are statistically significant between Column (3) and Column (4) and between Column (5) and Column (6), respectively. This supports our H4. Hence, the mitigating effect of Fintech on theft activities relies on the regional development level, indicating the possibility of broadening regional inequality.

Table 8: Mechanism Analysis (II)

	(1)	(2)	(3)	(4)	(5)	(6)
			Developed Regions	Underdeveloped Regions	High Unemployment	Low Unemployment
Dependent Variable	Theft Rate	Theft Rate	Theft Rate	Theft Rate	Theft Rate	Theft Rate
Fintech	0.6903* (0.3544)	−0.4189*** (0.1191)	−0.5663*** (0.1640)	−0.0561 (0.0931)	0.0193 (0.1165)	−0.6960*** (0.1743)
Fintech* log GDP per capita	−0.0026*** (0.0009)					
Fintech* unemployment rate		0.0431*** (0.0120)				
Control variables	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
City fixed effect	Yes	Yes	Yes	Yes	Yes	Yes
Observations	1,383	1,383	700	683	702	681
R-squared	0.2822	0.2781	0.2347	0.4779	0.3747	0.2521
No. of cities	286	286	143	143	146	140

Note: The control variables are the same as in Table 2. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The parentheses contain the standard errors clustered at the city level.

6. THE HEALTH COST OF THEFT ACTIVITIES

Finally, we attempted to estimate the cost of theft to victims to evaluate the social benefits of Fintech development in mitigating theft activities. Estimating the social cost of crimes is the key to designing public policies to fight against them. However, so far, there has been no systemic estimate of the cost of crimes in the PRC. The only exception is the study by Chen and Liu (2013), who utilized the statistical annuals to estimate the monetary cost of crime due to the loss of property, labor time loss of inmates, public security cost and lawyers' cost, and so on. However, criminal activities not only entail tangible losses for the victims but also impose considerable intangible losses. Miller, Cohen, and Rossman (1993) estimated that the mental health cost accounts for more than half of the social cost of household burglary for victims. Therefore, here, we attempted to estimate the intangible cost of theft for victims.

We employed the China Labor Dynamic Survey (CLDS) to investigate this issue. In 2016, the data covered 29 provinces and municipal cities, 158 cities, 11,631 households, and 21,086 adults. In this wave of the survey, the subjects were asked “in the past 12 months, did you have the experience of theft in the local area?” We used this information to construct a dummy variable, $Steal_i$, to indicate the individual recent experience of theft and employed the following equation (3) to examine the social cost of theft:

$$y_i = \alpha + \beta Steal_i + \gamma X_i + \eta Z_i + \delta urban_i + \varepsilon_i \quad (3)$$

y_i is the dependent variable for individual i , corresponding to a series of questions in the 2016 CLDS, including the trust level (from 1 to 4, 4 being the highest), happiness (from 1 to 5, 5 being the highest), the perception of safety (from 1 to 4, 1 being the safest), and the frequency of mental problems that the individual experienced in the past month (from 1 to 5, 1 representing no problem). X_i is a set of individual characteristics, including age, gender, marital status, income level, educational attainment, work status, hukou type, and self-reported physical health. Z_i is a set of household-level control variables, including the number of household members and the

household income. $urban_i$ is a dummy variable indicating that the household lives in an urban area, and ε_i is the robust standard error clustered at the community level.

Table 9 reports the ordered probit regression results based on equation (3). To facilitate the interpretation of the coefficients, it presents the marginal effect of the ordered probit model. It demonstrates that the experience of having something stolen significantly decreases the trust level, happiness, and perception of safety and increases the frequency of mental problems. Other things being equal, the victims of recent theft are 1.81% less likely to agree that most people are trustworthy, 3.8% less likely to feel very happy, 24.59% less likely to agree that the community is very safe, and 10.72% more likely to have experienced mental problems in the past month. These indicate a considerable intangible cost of theft for victims.

Table 9: The Cost of Theft for the Mental Health of Victims

Dependent Variable Ordered Probit	(1) Trust=4 (Strongly Agree)	(2) Happiness=5 (Very Happy)	(3) Safety=1 (Very Safe)	(4) Mental Problem=1 (No)
Whether stolen (yes=1)	-0.0181*** (0.0047)	-0.0380*** (0.0128)	-0.2459*** (0.0171)	-0.1072*** (0.0151)
Individual controls	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes
Urban dummies	Yes	Yes	Yes	Yes
Observations	19,913	19,914	19,914	19,914
Pseudo-R-squared	0.0629	0.0668	0.1073	0.0624

Note: The control variables include age, gender, marital status, income level, educational attainment, work status, hukou type, self-reported physical health, number of household members, and household income. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The parentheses contain the standard errors clustered at the city level.

Table 10 further employs OLS regression on equation (3) to examine the impact of the experience of theft on household consumption. We used the total household consumption in the past year as well as the total household medical expenses, respectively, as the dependent variables.³ Columns (1) and (2) report the regression results. It is apparent that the experience of having something stolen has no significant impact on consumption, perhaps due to the need to compensate for the lost property, but significantly increases the medical expenses by 29.54%. Given that the average household medical expenditure in the 2016 CLSD sample is 8,167 RMB, this implies that the victims of theft increase their medical expenditure by as much as 2,412 RMB a year.

Columns (3) and (4) employ panel data by merging the CLDS 2014 and 2016 data, which contain 7,870 repeated subjects. In addition to the control variables in equation (3), we added individual fixed-effect and city-level control variables as in equation (2). The magnitude of the coefficient is similar to that in Columns (1) and (2).

To deal with the possible confounders, in Columns (5) and (6), we further used a PSM-DID estimate to identify the consequences of theft for victims. We used the individual and household control variables in equation (3), including age, gender, marital status, income level, educational attainment, work status, hukou type, and self-reported physical health, as the covariates to match the victims of theft with other households. Based on whether households had experienced theft in 2016, we divided the households into a control group and a treatment group. The nearest-neighbor

³ We have also examined other categories of consumption, but they are not significant.

matching estimate results are similar, and the significantly increasing medical expenses further confirm the cost of theft for the mental health of victims. These results indicate the large intangible social benefits of Fintech development through the mitigating effect on theft activities.

Table 10: The Consumption Response of Victims of Theft

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent Variable	Log Total Consumption	Log Medical Expenses	Log Total Consumption	Log Medical Expenses	Log Total Consumption	Log Medical Expenses
Model	Multiple Sections	Multiple Sections	Panel Data	Panel Data	PSM-DID	PSM-DID
Whether stolen	0.0097 (0.0387)	0.2954*** (0.1394)	0.0225 (0.0398)	0.2541* (0.1353)		
Whether stolen*2016					0.0067 (0.0288)	0.2471** (0.1015)
Individual controls	Yes	Yes	Yes	Yes	Yes	Yes
Household controls	Yes	Yes	Yes	Yes	Yes	Yes
Individual fixed effect	\	\	Yes	Yes	Yes	Yes
Urban dummies	Yes	Yes	Yes	Yes	\	\
City controls	\	\	Yes	Yes	\	\
Observations	19,729	19,855	15,226	15,237	17,696	17,710
R-squared	0.2334	0.1129	0.2412	0.1027	0.0039	0.0020

Note: The control variables include age, gender, marital status, income level, educational attainment, work status, hukou type, self-reported physical health, number of household members, and household income. The city control variables are the same as those in Table 2. *, **, and *** represent statistical significance at the 10%, 5%, and 1% levels, respectively. The parentheses contain standard errors clustered at the city level.

7. CONCLUSION

This paper examined the impact of Fintech development on theft activities in the PRC. By utilizing a unique dataset on theft defendants during the period 2014–18, we showed that the development of Fintech has significantly mitigated the local theft activities, which we measured using the number of theft defendants in a particular year over the population. A 1 standard deviation increase in Fintech development is associated with a 0.39 standard deviation decrease in theft activities. This result held if we used the geographic distance from the city to Hangzhou to construct an instrumental variable for the diffusion of Fintech. The mitigating effect of Fintech is due to mobile payments and the new service jobs resulting from the development of Fintech. Finally, we showed that theft imposes a considerable mental health cost on victims. Our work indicated the unexpected social benefits from the mitigating effect of Fintech development on theft activities.

An important implication of this research is that the rapid development and diffusion of new technology may generate unexpected welfare implications for the society. Fintech has a wide scope, and we mainly focused on the digital finance aspect, specifically mobile payments and the associated e-commerce. Further work could explore the impact of other parts of Fintech. On the other hand, we showed that the mitigating effect of Fintech varies across regions, and the public security in more developed areas benefits more from Fintech. This points to possible widening regional inequality stemming from the so-called “digital gap,” which would be worthwhile studying in the future.

Moreover, research has observed that some crimes arise or become more salient in the Internet age, such as Internet fraud (Liang and Jiang 2020). This arouses curiosity about the relationship between the development of Fintech and other types of crime; for instance, does Fintech change the types of crime that a rational decision maker chooses? Though the demographic structure of theft defendants and inmates suggests that there are large differences between thieves and fraud criminals in terms of demographic characteristics and personalities (Zhang et al. 2014; Guo et al. 2020b), the question about criminals' possible substitution decision among different types of crimes is interesting and awaits future research.

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