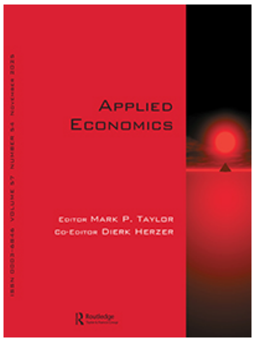

Applied Economics

ISSN: 0003-6846 (Print) 1466-4283 (Online) Journal homepage: www.tandfonline.com/journals/raec20

FinTech and crime: evidence from banks' partnering with Zelle

Bo Jiang & Jiawen Zhou

To cite this article: Bo Jiang & Jiawen Zhou (19 Aug 2025): FinTech and crime: evidence from banks' partnering with Zelle, Applied Economics, DOI: 10.1080/00036846.2025.2547111

To link to this article: https://doi.org/10.1080/00036846.2025.2547111

Published online: 19 Aug 2025.

APPLIED ECONOMICS
https://doi.org/10.1080/00036846.2025.2547111

Routledge
Taylor & Francis Group

FinTech and crime: evidence from banks' partnering with Zelle

Bo Jiang and Jiawen Zhou

Jiaotong-Liverpool University, Suzhou, China

ABSTRACT

We study how the rapid adoption of FinTech payment technology, Zelle, affects crime in the United States. We collect a novel dataset of Zelle's banking partners using an internet archive tool-the Wayback Machine. Our baseline OLS model shows a higher Zelle penetration is associated with a lower robbery rate and motor vehicle theft rate at the county level. To address the reverse causality issue, we exploit the fact that Zelle was launched by the seven largest U.S. banks in 2017. The difference-in-difference analysis shows that counties with large exposure to the seven largest U.S. banks before 2017 experienced a large decline in the robbery rate and motor vehicle theft rate. The negative effect on the robbery rate was more pronounced in counties with lower education levels and fewer law employees. Our findings shed light on the evolution of the social impact of FinTech adoption.

KEYWORDS

FinTech; crime; payment system; banking

JEL CLASSIFICATION

G20; G21; K42

I. Introduction

The rapid growth in mobile payments driven by the FinTech revolution has not only altered consumer habits but also significantly reduced dependence on cash (Snellman, Vesala, and Humphrey 2001). This shift has led to various societal changes. In this article, we investigate how the rapid adoption of the payment technology Zelle impacts crime in the U.S.

Zelle is the most widely used person-to-person (P2P) digital payment technology in the U.S. (Balyuk and Williams 2021). As Zelle is integrated into the mobile banking applications of its partnering banks, it encourages users to engage in online transactions.[1] Since its establishment in 2017, Zelle has experienced a steadily growing adoption rate, and by 2022, it was partnered with more than 1,800 U.S. banks and credit unions, covering about 80% of all U. S. bank accounts.[2] As a result of the continuous expansion of partnering banks, this may lead to a decline in the amount of physical currency circulating on the streets. This reduction in cash circulation might decrease the prevalence of street crimes, as there are fewer prime targets for criminals.

The main empirical challenge is collecting historical information on Zelle's banking partners. Zelle's official website only provides the current list of banking partners, without details on when each bank first joined the Zelle network. We overcome this problem by leveraging an internet archive tool-the Wayback Machine. The Wayback Machine allows us to collect information on when each banking partner first appeared on Zelle's website. We use the quarter in which the bank first appeared on the Zelle website as the time it joined the Zelle network. We also use FDIC summary of deposit data to construct a county-level Zelle penetration ratio and the FBI Uniform Crime Report (UCR) data to construct the county-level crime rate.

Our baseline specification finds that a higher Zelle penetration ratio is associated with a lower robbery rate and motor vehicle theft rate. To address the identification problem, we exploit the fact that Zelle was owned and launched by the seven largest U.S. banks. Our identification assumption is that the launch of Zelle is uncorrelated with local crime conditions and, thus, should be orthogonal to the crime rate. We construct the Big 7 banks' county-level exposure before 2017 and use a difference-in-difference (DiD) analysis to examine whether the launch of Zelle impacts crime. Indeed, we find that counties with a higher presence of the seven initiator banks experienced a

CONTACT Bo Jiang bo.jiang@xjtlu.edu.cn Jiaotong-Liverpool University, No. 8 Chongwen Road, Suzhou, P.R. China

[1]This is facilitated by the convenience and safety provided by Zelle for small savings, payments, and money transfers. They are free, fast, and convenient.

[2]Kate Fitzgerald, 'Zelle's Rocky Rise in 2022', American Banker, December 22, 2022. https://www.americanbanker.com/payments/list/zelles-rocky-rise-in-2022.

decline in robbery and motor vehicle theft rates. We test the parallel trend assumption by conducting a dynamic event study.

The heterogeneity analysis found that the decline in the robbery rate is more pronounced in counties with lower education levels and fewer law employees. We do not find significant heterogeneity in motor vehicle theft rate.

This article is related to a strand of the literature on the economic consequences of FinTech adoption. Zhu and Guo (2024) found that FinTech adoption in China boosts banks' performance. Qi, Ouyang, and Yu (2024) found that FinTech adoption improves firms' investment efficiency. Deng et al. (2024) show that FinTech adoption promotes rural household entrepreneurship. Hong, Lu, and Pan (2024) find that FinTech platforms might lead to performance-chasing behaviour in mutual fund distributions. While these studies focus on the effect of these third-party payment technologies, our study complements this strand of the literature by focusing on the effect of bank-affiliated payment technology, Zelle, on street crime.

This article is also related to a strand of the literature that focuses on payment technology, the shadow economy, and financial crimes. Schneider and Kearney (2013) argue that the adoption of payment technology in the public sector can lead to a decline in the shadow economy through more transparency and traceability provided by the payment system. Nan, Huang, and Zhao (2018) found that Chinese e-commerce platforms can be used to facilitate transaction-based tax evasion. Zhang et al. (2020) further used a deep learning approach to identify transaction-based tax evasion through social media websites. Huang, Nan, and Zhao (2022) give a comprehensive review of the financial crimes in the age of the digital economy and FinTech.

Our article is also closely related to the literature focusing on the social impact of the transition from cash to digital payments. The use of cash has historically facilitated certain types of crimes, particularly acquisitive crimes, such as street robberies and burglary (Armey, Lipow, and Webb 2014; Gandelman, Munyo, and Schertz 2023; Pridemore, Roche, and Rogers 2018; Rainone 2023; Warwick 1993; Wright et al. 2017). On the other hand, the increasing digitization of payments, represented by the growing use of credit cards, online transactions, and mobile banking, corresponds with a decrease in cash-related crimes. This shift has diminished the underground economy, money laundering, and tax evasion (Dalinghaus 2017; Deutsche Bundesbank 2017; Foley 2011; Giammatteo, Iezzi, and Zizza 2022; Gladisch 2017; Kruisbergen et al. 2019; Kuchciak 2013; Soudijn and Reuter 2016; Warwick 1993). Our article adds more evidence on the positive side of this cashless transition. We show that a higher Zelle penetration leads to less robbery and motor vehicle theft rates at the U.S. county level.

II. Data

Zelle Data

We assemble a novel data set that contains a list of Zelle-partnering banks from Zelle's current and historical websites.[3] Specifically, we use each bank's website provided by Zelle to obtain information about its headquarters and geographic location. If the linked website for each bank on Zelle is not accessible, we turn to Facebook, Twitter, and LinkedIn to find its headquarters and location information through the logo in the pop-out window on Zelle's website. Using each Zelle-partnering bank's headquarters and location information, we are able to match its record to find its unique identity number (RSSD ID) on the Federal Financial Institutions Examination Council (FFIEC) website. In total, there are 998 Zelle-partnering banks over the sample period of 2017Q3 to 2021Q4, among which 987 are successfully matched with their unique RSSD identified. The outcome from our matching process is comparable with Balyuk and Williams (2021), in which 1.7% of Zelle-partnering banks are not matched by FFIEC. Figure 1 plots the number of Zelle-partnering banks over time.

We use the Summary of Deposits data from FDIC to construct the county-level Zelle penetration ratio. Specifically, $ZellePen_{c,t}$ is constructed as the total deposits of Zelle-partnering banks in county c scaled by the total deposits in that county in year t. We standardized the Zelle penetration

[3]We use WayBack machine, a digital archive of the World Wide Web, to trace Zelle's historical websites.

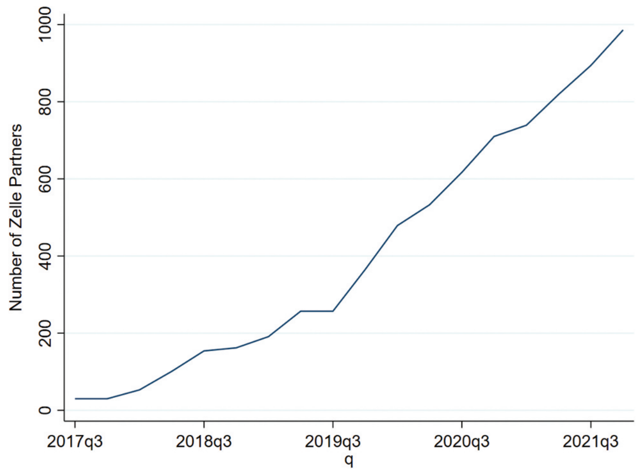

Figure 1. The number of Zelle-partnering banks over time.

ratio to ease our coefficient interpretation. Figure 2 plots the county-level Zelle penetration measure in the US in 2021.

Crime data

The crime data are collected from the Uniform Crime Reporting (UCR) Program of the Federal Bureau of Investigation (Federal Bureau of Investigation Crime Data Explorer, 2024). Initiated in 1908, this program provides standardized and reliable crime data from law enforcement agencies nationwide (5 Reasons Why the FBI Is So Effective, 2024). It offers a solid foundation for analysing and understanding crime trends on a national scale.

This investigation assembles the U.S. county-level annual data from 2012 to 2021. Data on offences include wealth-related crimes including robbery, burglary, larceny-theft, motor vehicle theft, and arson. Arson data are excluded from this study due to their limited availability. We focus on wealth-related crime because adopting a digital payment system is more likely to affect the wealth-related crime shown by Wright et al. (2017). We drop observations claimed as underreported, overreported or incomparable to previous years' data based on the footnotes of the report.

We compute the county-level crime rate as the number of offences in the county divided by the population in that county, then multiplied by 100,000. So the crime rate is interpreted as the number of offences per 100,000 people. We collect the annual county-level population data on the United States Census Bureau website.[4]

Control variable data

Our control variables include law enforcement employee rate, GDP, personal income, bachelor

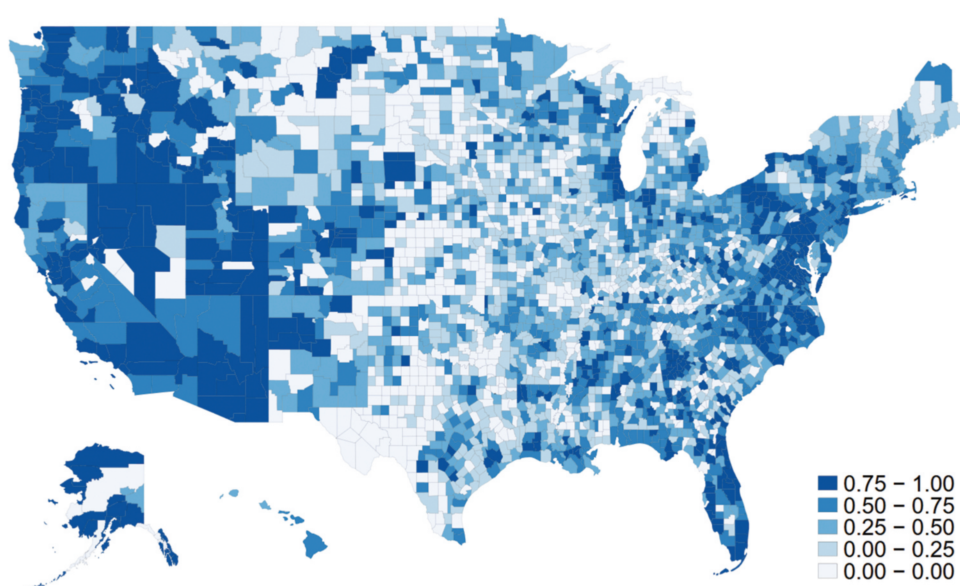

Figure 2. Zelle penetration in counties in 2021.

[4]United States Census Bureau (2024). https://data.census.gov/table.

Table 1. Summary Statistics.

	mean	sd	min	max	count
Robbery Rates	5.027	10.02	0.000	198.055	10416
Burglary Rate	151.872	153.17	0.000	3314.326	10416
Largency Rate	338.974	311.78	0.000	3395.784	10347
Motor Vehicle theft Rate	57.976	59.92	0.000	757.810	10416
Zelle Penetration	0.197	0.27	0.000	1.000	15774
Law Enforcement Employee Rate	3.625	2.75	0.561	17.078	11934
Branch Density	42.900	28.71	10.327	160.707	15281
Bachelor Ratio	14.064	5.47	5.200	31.200	15773
Ln(GDP)	13.947	1.56	10.939	18.291	15279
Ln(Population)	10.298	1.46	7.098	14.084	15282
Poverty Rate	15.931	7.19	4.800	47.100	15772
Age over 65 Rate	18.421	4.56	8.915	32.294	15411
Unemployment Rate	5.011	2.14	2.000	13.500	15773

This table presents the summary statistics of our sample period from 2017 to 2021. We list the definition of the variables in Appendix A.

ratio, poverty rate, and unemployment rate. All these control variables are at county level. We retrieve the law enforcement employee rate from FBI Uniform Crime Reporting (UCR) Program. We collect data for all other variables from U.S. Bureau of Economic Analysis (BEA)'s data archives. We list the definitions of these control variables in Appendix A.

Table 1 provides the summary statistics of data. The annual total crime rate is on average 732 per 100,000 persons per county. Property crime makes up a large share of total crime, followed by larceny theft and burglary. Murder and robbery are the least common offences in the datasets, with averages of approximately 1.7 and 5.5 incidents per 100,000 persons per county, respectively.

III. Methodology

In this section, we will lay out our general methodology to study how the adoption of Zelle affects the county-level crime rate. Though there are other FinTech applications similar to Zelle such as Venmo and Cash app, Zelle stands out as the only FinTech applications that are launched by commercial banks. Launched in 2017 by seven largest U.S. banks, Zelle quickly grows into a dominant player in P2P payment markets. The transaction volume processed by Zelle is larger than Venmo and Cash app combined.[5] Thus, we choose Zelle as an example to study the relationship between FinTech adoption and crime rate. We will use the sample from 2017 to 2021 since we can only collect the Zelle banking partner data through Wayback machine till 2017. In our subsequent DID analysis, we use the data from 2012 to 2021 as our main sample, 5 years before and after the launch of Zelle.

Baseline

Our baseline specification is as follows:

$$y_{c,t} = \beta ZellePen_{c,t-1} + X_{c,t-1}\gamma + \alpha_c + \alpha_t + \varepsilon_{c,t} \tag{1}$$

where the dependent variable is all different types of crime rate in county c in year t. $ZellePen_{c,t-1}$ is the Zelle penetration ratio in county c in year t-1. We lag one period to deal with the endogeneity issue. We standardized the Zelle penetration measure to ease coefficient interpretation. $X_{c,t-1}$ is a vector of control variables, including the county-level law enforcement employee rate, GDP, branch density, bachelor ratio, and poverty ratio. We include the county and time-fixed effects. The standard deviation is clustered at county level.

Reverse causality

The baseline specification might suffer the reverse causality issue. It could be possible that the crime rate might impact the adoption of Zelle. To address this endogeneity issue, we exploit the fact that Zelle was launched by the seven largest US banks. These seven largest banks operate nationally. The local crime rate is unlikely to be the main reason that these seven largest banks

[5]See the Forbes news report: https://www.forbes.com/sites/emilymason/2022/09/08/despite-a-late-start-bank-owned-zelle-moves-more-money-than-venmo-and-cash-app-combined/.

decided to launch the Zelle service at the first place. One concern is that the selection of the seven largest US banks as a basis for the DID analysis might also introduce endogeneity if some unobserved factors affect both the banks' geographical distribution and local crime rates. This issue can be mitigated if these unobserved factors are time-invariant. Our DID analysis, as well as county fixed effects, will absorb these unobserved county-specific factors. In addition, the time fixed effects will absorb these time-variant common macro trend that might affect the crime rate such as inflation and economic growth. We also conduct a parallel trend analysis to further attenuate this issue.

We construct county-level penetration rate for the seven largest US banks using the Summary of Deposit (SOD) from FDIC. Thus, we have the following specifications:

$$y_{c,t} = \gamma Post_t \times ZellePenBig7_c + \Gamma \mathrm{X}_{\mathrm{c,t-1}} + \alpha_{\mathrm{c}} + \alpha_{\mathrm{t}} + \varepsilon_{\mathrm{ct}} \tag{2}$$

Where $Post_t$ is a dummy variable that is 1 after 2017 and 0 otherwise, the sample period for this specification is from 2012 to 2021. $ZellePenBig7_c$ is the seven largest US banks' penetration ratio in county c as of 2017. The control variables are the same as our benchmark specification. We also include the county and year fixed effects.

We employ dynamic event study analysis to examine the parallel trend assumption. We only conduct dynamic event studies for the crime rate that are significantly impacted by the Zelle adoption at the county level, namely crime rate and motor vehicle theft rate.

Heterogeneity analysis

We conduct a heterogeneity analysis to see how Zelle adoption affects the robbery rate in counties with different characteristics. The specification is as follows:

$$y_{c,t} = \alpha Post_t \times ZellePenBig7_c \times X_{ct} + \gamma Post_t \times ZellePenBig7_c \times X_{ct-1} + Post_t \times X_{ct-1} + \Gamma \mathrm{X}_{\mathrm{ct-1}} + \alpha_{\mathrm{c}} + \alpha_{\mathrm{t}} + \varepsilon_{\mathrm{ct}} \tag{3}$$

We add a triple interaction term into the model including the law enforcement employee rate, GDP, personal income, bachelor ratio and poverty ratio. The control variables are the same as our benchmark specification. We also include the county and year fixed effects.

IV. Result and discussion

Benchmark specification

We report our benchmark results in Table 2. Column (1) shows that one standard deviation increase in Zelle penetration is associated with a 0.557 incidence decline in robbery per 100,000 people. The result is significant at a 1% level. Column (4) shows that one standard deviation increase in Zelle penetration is associated with a 2.024 incidences decline in motor vehicle theft per 100,000 people. The result is significant at a 1% level. The results are consistent with the argument by Rogoff (2017), where he argues that large-denomination bills can aid crime and tax evasion. Since motor vehicle is the common place to store cash and personal belongings, the negative effect of Zelle penetration on motor vehicle rates reveals that substituting away from cash through the adoption of Zelle could be the channel that leads to the reduction of these crimes.

Reverse causality

We report our DID results in Table 3. The dependent variables in column (1) and column (2) are robbery rate and motor vehicle theft rate, respectively. Specifically, a one standard deviation increase in Big 7 penetration rates in the county is associated with a decline in robbery of 0.515 incidence per 100,000 people and a decline in motor vehicle theft rate of 1.360 incidences per 100,000 people. The result for the robbery rate is significant at the 1% level, and the result for motor vehicle theft rate is significant at the 5% level. The results are consistent with our benchmark results.

We plot the coefficients of dynamic event study for robbery and motor vehicle theft crime in Figures 3 and 4. The coefficients before 2017 are insignificant from 0, suggesting there are no prior trends. Both crimes significantly drop after the introduction of Zelle in 2017.

Table 2. The impact of Zelle penetration on crimes.

	(1) Robbery	(2) Burglary	(3) LarcenyTheft	(4) MotoTheft
L.ZellePen	−0.559***	−0.842	−1.610	−2.012 **
	(0.000)	(0.789)	(0.589)	(0.012)
L.LawEmployee	0.156 *	0.248	4.071	1.145
	(0.089)	(0.884)	(0.110)	(0.187)
L.Branch Density	−0.0952	1.066 ***	0.744	0.302
	(0.118)	(0.009)	(0.398)	(0.120)
L.Bachelor	0.00157	−1.096	−0.0616	−1.883 ***
	(0.985)	(0.592)	(0.981)	(0.003)
L.LnGDP	−2.962 **	36.40	38.07	−5.543
	(0.036)	(0.241)	(0.221)	(0.559)
L.LnPop	8.675*	−279.1 **	−341.9 ***	−30.31
	(0.067)	(0.044)	(0.009)	(0.385)
L.Poverty Rate	0.00734	1.553	−0.123	−0.774 **
	(0.897)	(0.167)	(0.927)	(0.042)
L.Age over 65 Ratio	−0.0124	−6.236 *	−3.985	0.603
	(0.940)	(0.079)	(0.369)	(0.566)
L.Unemployment Rate	0.0878	3.599 **	2.490	−0.551
	(0.522)	(0.021)	(0.367)	(0.560)
County FE	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes
Observations	8669	8669	8620	8669
Adj R^2	0.690	0.743	0.862	0.735
RMSE	5.513	77.16	114.5	31.00

This table reports the regression results of different types of crime on the Zelle penetration in the county level. The ZellePen is county-level Zelle penetration calculated as the ratio of the Zelle partner's deposit in the county divided by the total deposits in the county. ZellePen is standardized. p-values in parentheses. ***, **, and * denote statistical significance levels at 1%, 5%, and 10% levels. The standard deviation is clustered at county level.

Table 3. The impact of seven Zelle initiators penetration on crimes.

	(1) Robbery	(2) MotoTheft
ZellePenBig7*Post	−0.488 ***	−1.538 **
	(0.001)	(0.025)
L.LawEmployee	0.00514	−0.0195
	(0.127)	(0.163)
L.Branch Density	−0.0114	0.247 **
	(0.392)	(0.024)
L.Bachelor	−0.0303	−1.181 ***
	(0.597)	(0.005)
L.LnGDP	0.0508	10.16 **
	(0.939)	(0.037)
L.LnPop	−0.221	−35.76 **
	(0.926)	(0.016)
L.Poverty Rate	−0.0345	−0.268
	(0.341)	(0.253)
L.Age over 65 Ratio	−0.107	0.790
	(0.220)	(0.163)
L.Unemployment Rate	0.207 ***	−1.403 ***
	(0.002)	(0.001)
County FE	Yes	Yes
Year FE	Yes	Yes
Observations	19270	19270
Adj R^2	0.629	0.669
RMSE	6.724	32.78

This table reports the regression results of robbery and motor vehicle theft rate on the Zelle penetration in the county-level. The ZellePenBig7 is the county-level penetration rate for the seven Zelle initiators in 2017. ZellePenBig7 is standardized. P-values in parentheses. ***, **, and * denote statistical significance level at 1%, 5%, and 10% levels. The standard deviation is clustered at county level. The variables are defined in Appendix A.

One concern is our results might be contaminated by other confounding factors and broader economic trends. First, there are other payment technologies competing with Zell such as Venmo, which is a confounding factor that might affect our results. We argue our DID analysis will not be affected as long as the adoption of Venmo is steady and does not experience a significant jump before and after 2017. Indeed, the monthly new users and transaction volumes constructed by Unger et al. (2020) show that there is no

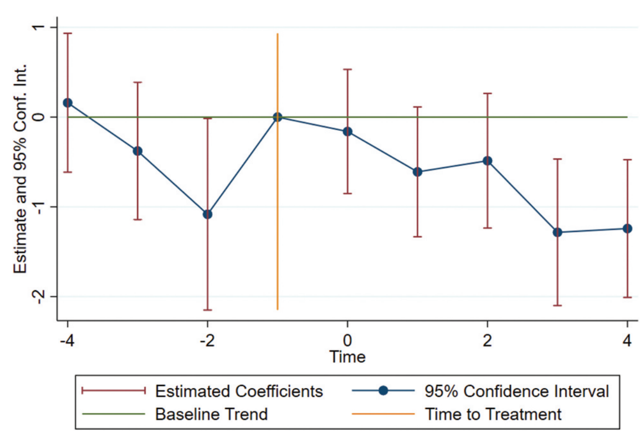

Figure 3. Event-study estimates for robbery crime rates in the US. This figure presents the coefficients of the dynamic event study, where the dependent variable is the county-level robbery rate and the main independent variable is the seven largest US banks' penetration ratio in county c as of 2017. The control variables are the same as our benchmark specification. We also include the county and year fixed effects.

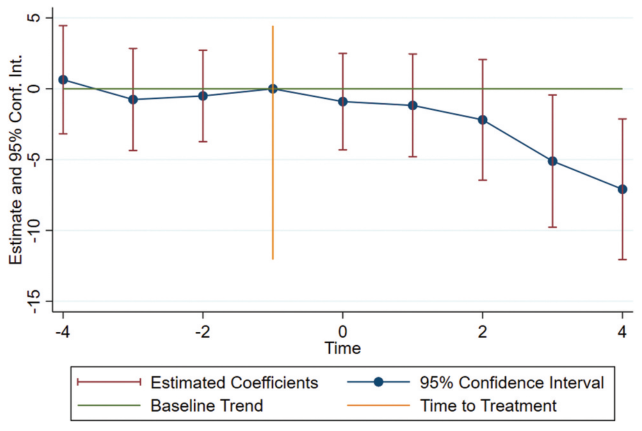

Figure 4. Event-study estimates for motor vehicle crime rates in the US. This figure presents the coefficients of the dynamic event study, where the dependent variable is the county-level motor vehicle crime rate and the main independent variable is the seven largest US banks' penetration ratio in county c as of 2017. The control variables are the same as our benchmark specification. We also include the county and year fixed effects.

significant jump before and after 2017. Second, we incorporate the time-fixed effects, which already absorb all these time-varying nation wide common trends.

Heterogeneity analysis

We conduct a heterogeneity analysis to see how different county characteristics affect the robbery rate and motor vehicle theft rate. Results in Table 4 show that the crime attenuation effect of Zelle adoption is more pronounced in counties that have fewer law employees. This result is consistent with a police deterrence theory studied by Braga et al. (2019)), where they find hotspot policing to be an effective way to prevent crime. In an area with more law enforcement employees, robbery is deterred and, thus, the effect of Zelle on the robbery rate declines. We also find the negative effect of Zelle adoption on the robbery rate is less pronounced in counties that have more educated population. The result is consistent with the theory proposed by Lochner (2004), where he shows more education increases the opportunity cost of perpetrating a crime. Thus, the negative effect of Zelle on the robbery rate is small in the counties with a higher proportion of the educated population. We do not find significant heterogeneity in motor vehicle theft rate.

Table 4. The impact of Zelle penetration on robbery: heterogeneity analysis.

	(1) Robbery Rate	(2) Robbery Rate
L.ZellePen	−0.561 ***	−1.018 ***
	(0.000)	(0.001)
L.ZellePen*L.LawEmployee	0.00125 **	
	(0.022)	
L.ZellePen*L.Bachelor		0.0298 **
		(0.045)
County FE	Yes	Yes
Year FE	Yes	Yes
llawemprate	Yes	Yes
Observations	8669	8669
Adj R^2	0.690	0.690
RMSE	5.514	5.512

This table presents the results of regressing the Robbery rate on the interaction of ZellePenBig7 and counties' one-year lagged characteristics. All continuous variables are winsorized at the 1th and 99th percentiles. All continuous variables are winsorized at the 1th and 99th percentiles. The standard deviation is clustered at the bank level. The variables are defined in Appendix A. P-values in parentheses. ***, **, and * denote statistical significance levels at 1%, 5%, and 10% levels.

V. Conclusion

We investigate the impact of FinTech adoption on the crime rate in the US through the rapid adoption of Zelle. We assemble a novel dataset of Zelle banking partners through an internet archive tool, Wayback machine.

We find that counties with high Zelle penetration rate experienced a decline in robbery rate and motor vehicle theft rate. To address the reverse causality issue, we take advantage of the fact that Zelle was launched by the seven largest US banks in 2017. The launch of this technology is unlikely to be driven by tackling the crime issue where these banks operate nationally. We find that counties with high Big 7 presence experienced a larger decline in robbery rate and motor vehicle theft rate compared to counties with low Big 7 presence. Our results shed light on the continued evolution of the social impact of cashless society through the lens of FinTech adoption.

While our study provides evidence of the positive social impact of FinTech adoption, the adoption of Zelle also poses a series of challenges, such as financial fraud. For example, a recent report from CFPB claims that customers lost more than $870 million dollars till 2024. [6] More research needs to be done regarding customer protection, cybercrime, and cybersecurity-related issues. Another challenge is the digital divide between young people and old.

[6]See the report: https://www.cbsnews.com/news/zelle-fraud-chase-bank-of-america-wells-fargo-cfpb-payments/.

Young people typically are more likely to adopt this payment technology than elders. As the adoption of payment technology picks up, whether banks opt to shut down their branches. If they do, how that might impact the elders and people without a banking account? The effect of this digital transformation on financial inclusion is another area that demands more research.

Disclosure statement

No potential conflict of interest was reported by the author(s).

Funding

The research is funded by the Research Development Fund (RDF) from Xi'an Jiaotong-Liverpool University. The fund is provided to hire research assistants. The grant number is RDF-21-02-081; Xi'an Jiaotong-Liverpool University [Research Developmenet Fund RDF-21-02-081].

Data availability statement

The data that support the findings of this study are available from the corresponding author, Bo Jiang(bo.jiang@xjtlu.edu.cn), upon reasonable request. This article follows the Basic, Share upon Request policy.

References

Armey, L. E., J. Lipow, and N. J. Webb. 2014. "The Impact of Electronic Financial Payments on Crime." *Information Economics and Policy* 29:46–57. https://doi.org/10.1016/j.infoecopol.2014.10.002.

Balyuk, T. and E. Williams. 2021. Friends and Family Money: P2P Transfers and Financially Fragile Consumers. *Available at SSRN 3974749*.

Braga, A. A., B. S. Turchan, A. V. Papachristos, and D. M. Hureau. 2019. "Hot Spots Policing and Crime Reduction: An Update of an Ongoing Systematic Review and Meta-Analysis." *Journal of Experimental Criminology* 15 (3): 289–311. https://doi.org/10.1007/s11292-019-09372-3.

Dalinghaus, U. 2017. *Keeping Cash: Assessing the Arguments about Cash and Crime*. Irvine, CA: Institute for Money, Technology & Financial Inclusion.

Deng, X., S. Chi, L. Yao, and J. Zou. 2024. "Fintech and Rural Household Entrepreneurship." *Finance Research Letters* 68:106026. https://doi.org/10.1016/j.frl.2024.106026.

Deutsche Bundesbank. 2017. *War on Cash: Is There a Future for Cash?* International Cash Conference 2017, Mainau Island, Germany. Deutsche Bundesbank. https://www.bundesbank.de/resource/blob/710118/6bab368611007785b02fbb008f368cf7/472B63F073F071307366337C94F8C870/war-on-cash-data.pdf.

Foley, C. F. 2011. "Welfare Payments and Crime." *Review of Economics and Statistics* 93 (1): 97–112. https://doi.org/10.1162/REST_a_00068.

Gandelman, N., I. Munyo, and E. Schertz. 2023. "Does Paying with Cards Reduce Crime at Stores? Evidence from a Targeted Cash Ban in Uruguay." *Journal of Law & Economics* 66 (1): 1–20. https://doi.org/10.1086/721910.

Giammatteo, M., S. Iezzi, and R. Zizza. 2022. "Pecunia Olet. Cash Usage and the Underground Economy." *Journal of Economic Behavior and Organization* 204:107–127. Cash Usage and the Underground Economy (October 19, 2021). Bank of Italy Occasional Paper (649).https://doi.org/10.1016/j.jebo.2022.10.005.

Gladisch, E. 2017. "The Use of Cash in Germany: Status and Outlook." *Cash in East Asia* 44:133–151. https://doi.org/10.1007/978-3-319-59846-8_9.

Hong, C. Y., X. Lu, and J. Pan. 2024. "Fintech Platforms and Mutual Fund Distribution." *Management Science*. https://doi.org/10.1287/mnsc.2022.01966.

Huang, E., X. Nan, and J. Zhao. 2022. "Financial Crimes in the Age of the Digital Economy and FinTech." *Global Perspectives in FinTech: Law, Finance and Technology*, edited by H.Y. Chen, P. Jenweeranon, and N. Alam, 51–77. Palgrave Macmillan, Cham: Springer.

Kruisbergen, E. W., E. R. Leukfeldt, E. R. Kleemans, and R. A. Roks. 2019. "Money Talks: Money Laundering Choices of Organized Crime Offenders in a Digital Age." *Journal of Crime & Justice* 42 (5): 569–581. https://doi.org/10.1080/0735648X.2019.1692420.

Kuchciak, I. 2013. "E-Money and Electronic Payments as a Way of Reducing the Shadow Economy." *Changes in Social and Business Environment* 5:55–62.

Lochner, L. 2004. "Education, Work, and Crime: A Human Capital Approach." *International Economic Review* 45 (3): 811–843. https://doi.org/10.1111/j.0020-6598.2004.00288.x.

Nan, X., E. Huang, and J. Zhao. 2018. "Transaction-Based Tax Evasion on Chinese e-Commerce Platforms: Compliance Difficulties for Three Types of Taxes, VAT Reform, and New Winners." *Journal of Chinese Tax and Policy* 8 (1): page forthcoming.

Pridemore, W. A., S. P. Roche, and M. L. Rogers. 2018. "Cashlessness and Street Crime: A Cross-National Study of Direct Deposit Payment and Robbery Rates." *Justice Quarterly* 35 (5): 919–939. https://doi.org/10.1080/07418825.2018.1424923.

Qi, Y., L. Ouyang, and Y. Yu. 2024. "The Impact of Fintech Adoption on Corporate Investment: Evidence from China." *Finance Research Letters* 67:105929. https://doi.org/10.1016/j.frl.2024.105929.

Rainone, E. 2023. "Tax Evasion Policies and the Demand for Cash." *Journal of Macroeconomics* 76:103520. https://doi.org/10.1016/j.jmacro.2023.103520.

Rogoff, K. 2017. *The Curse of Cash: How Large-Denomination Bills Aid Crime and Tax Evasion and Constrain Monetary Policy*. Princeton, NJ: Princeton University Press.

Schneider, F., and A. Kearney. 2013. *The Shadow Economy in Europe, 2013*. Chicago, IL: Johannes Kepler Universitat, Linz.

Snellman, J. S., J. M. Vesala, and D. B. Humphrey. 2001. "Substitution of Noncash Payment Instruments for Cash in Europe." *Journal of Financial Services Research* 19 (2–3): 131–145. https://doi.org/10.1023/A:1011151219545.

Soudijn, M., and P. Reuter. 2016. "Cash and Carry: The High Cost of Currency Smuggling in the Drug Trade." *Crime, Law, & Social Change* 66 (3): 271–290. https://doi.org/10.1007/s10611-016-9626-6.

Unger, C., D. Murthy, A. Acker, I. Arora, and A. Chang. 2020. "Examining the Evolution of Mobile Social Payments in Venmo." *International Conference on Social Media and Society*, Toronto, ON, Canada, 101–110.

Warwick, D. R. 1993. *Reducing Crime by Eliminating Cash*. San Francisco, CA: National Council on Crime and Delinquency. Accessed August 13, 2025. https://files.eric.ed.gov/fulltext/ED377114.pdf.

Wright, R., E. Tekin, V. Topalli, C. McClellan, T. Dickinson, and R. Rosenfeld. 2017. "Less Cash, Less Crime: Evidence from the Electronic Benefit Transfer Program." *Journal of Law & Economics* 60 (2): 361–383. https://doi.org/10.1086/693745.

Zhang, L., X. Nan, E. Huang, and S. Liu. 2020. *Detecting Transaction-based Tax Evasion Activities on Social Media Platforms Using Multi-modal Deep Neural Networks*. ArXiv:2007.13525. ArXiv preprint. Accessed, August 13, 2025. https://arxiv.org/abs/2007.13525.

Zhu, K., and L. Guo. 2024. "Financial Technology, Inclusive Finance and Bank Performance." *Finance Research Letters* 60:104872. https://doi.org/10.1016/j.frl.2023.104872.

Appendix

Appendix A. Variable definitions

The law enforcement employee rate is calculated as law employee per 1000 person times 1000 divided by the population. The Law Enforcement Employees dataset consists of yearly gathered data on law enforcement officers and non-officer personnel working within law enforcement agencies. It includes details on the count of officers and civilians employed, as well as the ratio of law enforcement employees per county population. According to the Uniform Crime Reporting (UCR) Program, law enforcement officers are defined as individuals typically equipped with firearms and badges, possessing full arrest authority, and receiving payment from designated governmental funds allocated for sworn law enforcement roles.

Real GDP data are available annually for each county, presented in thousands of chained 2017 dollars. It consists of the total GDP of all industries, including both private industries and government sectors within each county.

Population data provide estimates of the number of individuals, including both civilian and military, residing in each county.

Personal Income refers to the total income received by individuals, consisting of earnings from their provision of labour, land, and capital used in the current production, along with other sources of income such as personal current transfer receipts.

The Ratio of Bachelor's degree represents the estimated proportion of individuals aged 25 years and over who have attained a bachelor's degree within each county. The percentage is calculated by dividing the number of individuals in this age group with a bachelor's degree by the total number of individuals aged 25 years and over.

The Poverty Rate denotes the percentage of individuals below the poverty level within each county. Following the guidelines outlined in the Office of Management and Budget's (OMB) Statistical Policy Directive 14, the Census Bureau utilizes a set of income thresholds that vary based on family size and composition to ascertain poverty status. If a family's total income lower than the designated threshold, all members of that family are classified as living in poverty.

The county-level unemployment rate data come from the Bureau of Labor Statistics (BLS) Local Area Unemployment Statistics (LAUS) program, which is based on concepts and definitions from the Current Population Survey (CPS). According to the CPS, individuals are classified as unemployed if they are jobless, have actively sought work in the past 4 weeks, and are available to work. Those on temporary layoff awaiting recall are also included. The unemployment rate represents the percentage of unemployed individuals in the labour force.