Crypto ATMs:
Material Effects of Virtual Currencies*

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Abstract

How cryptocurrencies from the cyberspace influence household finance and the real world? We investigate the economic consequences of cryptocurrency adoption by the main street enabled by crypto ATM installation. Using a unique, hand-collected dataset, we identify a plausibly causal relationship between the staggered rollout of crypto ATMs and regions' increased crypto activity and financial participation, as well as an associated increase in local cybercrime and financial frauds. Our findings are especially pronounced on platforms facilitating monetary transactions and in regions with limited banking infrastructure, indicating that crypto ATMs function as shadow intermediaries primarily for unbanked and low-income households. A back-of-the-envelope estimate suggests a net welfare gain, but with unequal distribution. Overall, our findings reveal that cryptocurrencies adoption beyond the FinTech-savvy and blockchain-enthusiastic exerts material impacts on the real economy, disrupting traditional financial sectors by expanding market participation in both cryptocurrencies and stocks, while unintentionally increasing (cyber)crimes.

Keywords: Banking, Crimes, Cryptocurrency, Financial Inclusion, FinTech Adoption, Household Finance, Small Businesses.

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1 Introduction

By mid-2025, the price of Bitcoin had exceeded $120,000, bringing the total market capitalization of cryptocurrencies to more than $4 trillion USD. Stablecoins and real world asset tokenization (RWA) have also piqued public interest lately; led by the United States, many governments and institutions start to embrace crypto assets and Decentralized Finance (DeFi). However, it remains unclear whether cryptocurrencies have been widely adopted as privacy-preserving digital cash, despite purported to increase financial inclusion with new technologies (Philippon, 2019; Harvey, Ramachandran and Santoro, 2021). While some benefit from its rapid proliferation (Makarov and Schoar, 2025), the potential harms lurk in the background, posing regulatory challenges (Foley et al., 2019; Cong et al., 2023; Ferreira et al., 2023; Cong et al., 2025; Griffin and Mei, 2024). More generally, we lack systematic evidence on how a technology that began as an "enthusiasts' plaything" in cyberspace is affecting financial markets, the real economy, and society.

To this end, we provide a comprehensive examination of the ramifications of cryptocurrency access and usage by the broader populace, leveraging a plausibly causal relationship between the rollout of crypto ATMs and regional economic activities. We provide the first piece of evidence that general cryptocurrency adoption significantly increase household participation in financial markets, both crypto and traditional, and local business creation. We document that crypto ATMs function as a shadow banking infrastructure, substituting for declining brick-and-mortar branches and reshaping the competitive landscape for intermediaries. But the noticeable increase in cybercriminal activities, financial frauds, drug abuse, and gun violence render crypto ATMs a double-edged sword. At the core of such financial innovations is a welfare tradeoff whereby reduced participation frictions increase access but weaken oversight, complicating crime control and regulatory enforcement. While the gains are accrued to marginal adopters (unbanked, low-income households, and certain minorities), the costs of fraud are often externalized across the broader system, creating redistribution. Our findings offer initial insights into the complex ramifications of broader cryptocurrency adoption on the economy and society.

Crypto ATMs, also known as Bitcoin ATMs or BTMs, were first introduced in Canada on October 29, 2013, and have since expanded rapidly across the globe. Since 2014, these machines began appearing in everyday locations across the United States, often located near residential areas for convenient access. By the end of 2022, the United States has over 30,000 crypto ATMs. As crypto ATMs offer a convenient, 24/7 service to purchase cryptocurrency with cash or debit cards, they have been widely embraced by cryptocurrency users. Moreover, crypto ATMs provide individuals with alternative access to the crypto market, allowing participation without relying on centralized exchanges. However, despite these advantages, crypto ATMs remain largely unregulated. In many cases, installing a crypto ATM does not require a business license. Since transactions on crypto ATMs usually do not require personal identification, the installation of crypto ATMs allow anonymous and unregulated transactions that criminals may take advantage of.[1]

Our empirical analysis begins with a unique, manually constructed dataset containing detailed information on crypto ATMs, including their geographic coordinates (longitude and latitude), installation dates, and, where applicable, removal dates. We also obtain an individual-level daily app usage dataset, which includes the user's location when opening the app, the duration of app usage, and basic demographic information. By analyzing the usage pattern of crypto-related apps such as *CoinBase* or *Crypto.com*, we can easily measure and identify how crypto ATMs influence participation in the cryptocurrency market. We also include stock-trading apps' usage (e.g., *Robinhood* or *Yahoo Finance*) as measurement of engagement in the stock markets. To capture regional cybercriminal activities, we utilize data on crime reports (e.g., identity theft) by the U.S. law enforcement agencies. Finally, we collect data on consumer reports of complaints and inquiries related to financial services, which provide detailed information on the originating zip codes, key issues addressed, and dates of submission.

Our empirical strategy primarily entails a Bartik-style shift-share instrumental variable for causal identification. The intuition is that crypto ATMs generally serve a population near the machines only, and are unlikely installed due to cryptocurrency demand elsewhere. However, installations in highly economically interconnected counties may exert indirect influence, with demand potentially being "transmitted" across county borders, serving as an effective instrument for identification. Specifically, we use the total value of small business loans issued by non-focal counties prior to 2013 as a proxy for the economic connectivity between counties to construct the Bartik-style instrumental variable for the number of crypto ATMs in each county. This loan-based measure serves as the weighting factor in capturing inter-county economic linkages. As a robustness check, we also introduce an alternative instrumental variable, defined as street density measured in 2011 multiplied by the Bitcoin price at the close of each year-quarter.[2]

[1]There are some examples of the potential risks of cybercrimes performed using crypto ATMs: https://www.cnbc.com/2024/09/08/biggest-risks-of-accessing-crypto-through-bitcoin-atm.html

[2]The main results are also similar using this alternative instrument. These results are documented in

The first set of empirical results reveal regional engagement in cryptocurrency markets. Using individual-level app activity data, we find that the installation of one additional crypto ATM in a county is associated with a 0.12% increase in the probability of individuals participating in the cryptocurrency market, equivalent to approximately 150 additional participants per county. These results remain both economically meaningful and statistically significant after controlling for more granular fixed effects, including ZIP code-level and individual-level fixed effects, and the estimated effect size does not vary significantly across different empirical settings.

We assess the robustness of our results using alternative specifications that examine individual behavior following the installation of the first crypto ATM near a user's residence. Using a difference-in-differences approach focused on individuals with no prior exposure to crypto ATMs at the start of our sample period, we find that the presence of a crypto ATM in a user's zip code increases the likelihood of engaging in the cryptocurrency market by 0.71%. Employing an event-study framework with individual-level fixed effects, we confirm that our results satisfy the parallel trends assumption. Notably, individuals residing in neighborhoods with newly installed crypto ATMs exhibit a 2% higher probability of market engagement two years after installation. These findings remain robust when we expand the control group to include individuals from early treated zip codes, defined as those where crypto ATMs were installed two years prior to the start of our observation window.

Applying similar empirical specifications, we extend our analysis to examine participation in stock-related applications. Our results reveal a positive correlation between crypto ATM installations and increased stock market participation, although this relationship is statistically less significant than the effect observed for cryptocurrency market participation. These findings suggest that the installation of crypto ATMs contributes to broader financial participation, influencing not only the activity within the cryptocurrency market but also the engagement with traditional financial assets such as equities.

A recent literature studies how household finance influences decisions to engage in entrepreneurial activities (Adelino et al., 2015, 2017). To add to this understanding, we next investigate the formation of business as a downstream effect of heightened financial market participation. As entry costs into the digital asset ecosystem decline, we hypothesize that an increase in the number of crypto ATMs facilitates greater entrepreneurial activity. To test this hypothesis, we analyze county-level startup rates across the United

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States. Our findings indicate that the installation of one additional crypto ATM is associated with approximately 0.003 new firm registrations per 1,000 residents during the pre-COVID period, or an estimated $1,527 in small business formation value.

Overall, our findings suggest that the installation of crypto ATMs contributes to an overall increase in financial engagement. However, this expansion also raises important questions about potential risks associated with the growing presence of crypto ATMs. To address these, we investigate the changes in crypto-enabled financial crimes using a difference-in-differences approach on policy agency-level data concerning reported cybercrime incidents. Our analysis reveals that following the installation of crypto ATMs, the incidence of identity theft increased by 0.02 cases per 1,000 capita. Notably, we do not observe significant effects across other categories of cybercrime, such as welfare fraud, online gambling, or blackmail. This pattern likely reflects the tendency for criminals to exploit crypto ATMs predominantly for financial fraud, most commonly in the form of identity theft.

The consumer reports dataset leads to a similar conclusion when examined from the victims' perspective. With a Bartik-style instrumental approach, we find a significant correlation between the installation of crypto ATMs as well as regional financial fraud reports for three of the major categories, including information leakage, suspicious transaction, as well as fraudulent debt. We supplement our analysis by using a zipcode-level difference-in-differences approach and find a consistent result: after the installation of crypto ATMs, a noticeable increase in regional financial fraud complaints is observed in the corresponding zip codes. The evidence strongly suggests a causal relationship between the installation of crypto ATMs and the increase in financial fraud.

We further extend our analysis by classifying financial frauds according to the types of firms involved to better understand the disruption within the financial industry. Our results show that a significant portion of the observed effect stems from complaints against traditional financial institutions such as banks, suggesting that criminals use cryptocurrency transactions to steal private information, including bank account details. This finding implies that the proliferation of cryptocurrency poses a threat to the traditional financial sector. The reputations of investment and asset management firms, as well as online lending companies, are similarly affected by the presence of crypto ATMs. Moreover, complaints against FinTech companies have also increased markedly.

We conclude our investigation of the negative impacts of crypto ATM introduction by examining its broader socioeconomic consequences of on local economic and social activities. Our analysis reveals a positive correlation between the presence of crypto ATMs and regional overdose-related deaths, while no significant association is observed with alcohol-related fatalities. In addition, we document an increase in gunshot incidents. These findings suggest that the unregulated nature of cryptocurrency trading may pose substantial societal risks, extending beyond financial fraud to adversely affect public health, safety, and overall well-being.

Fundamentally, why do people use crypto ATMs? We present compelling evidence that these machines are often installed as shadow intermediaries to serve unbanked individuals, replicating bank-like services without regulation. Their expansion demonstrates how decentralized finance penetrates the "last mile" of intermediation. Two key findings support this mechanism. First, our empirical analysis reveals that the effects of both financial engagement and financial fraud-related behaviors are significantly more pronounced in regions with limited access to conventional banking services. This geographic heterogeneity suggests that individuals may turn to the crypto market as an alternative to fiat-based financial infrastructure. Second, we observe a positive correlation between the closure of traditional bank branches and the subsequent installation of crypto ATMs. This pattern further implies that crypto ATM providers may strategically deploy their machines to fill the diminishing banking access.

Consistent with this perspective, our study focuses on the local physical adoption of cryptocurrencies among individuals who are not tech-savvy or crypto enthusiasts, the very marginal adopters most affected by participation barriers. While cryptocurrency offers the appeal of digital cash with privacy, its adoption typically requires a certain level of technical knowledge, unlike traditional cash, which is universally accessible. By introducing crypto ATMs, we observe how reducing this adoption barrier affects usage among the general public. Our findings indicate that crypto ATMs primarily benefit those previously excluded from digital finance, and do not significantly impact tech-savvy individuals, who are likely already engaged in other asset classes and are not the primary target for increased adoption.

Our paper contributes to several active areas of research. First, our study adds to the growing literature on cryptocurrency adoption. As the cryptocurrency market is highly decentralized and democratized (Makarov and Schoar, 2022), prior studies build theoretical frameworks to explain the behaviors of cryptocurrency investors, particularly their onchain behavior (Kogan et al., 2024; Foley et al., 2019; Cong and He, 2019; Cong et al., 2021; Sockin and Xiong, 2023; Liu et al., 2023; Makarov and Schoar, 2025). Fang and

Huang (2022) surveys the literature in accounting and finance. Other studies show how people participate in the stablecoin market (Ma et al., 2025). In our paper, we analyze the impact of cryptocurrency from the perspective of its effects on the real and offline economy. We demonstrate that the installation of cryptocurrency ATMs increases individuals' awareness of these alternative assets and the financial market in general, thereby fostering financial inclusion, which aligns with the theoretical discussions such as Philippon (2019). This enhanced inclusion may lead to capital gains through increased participation in both the cryptocurrency market and traditional equity markets, a channel not documented in the existing literature.

Second, we offer evidence illustrating how financial innovations can foster criminal behavior. Other related research provides comprehensive analyzes on what incentivizes people to commit criminal behavior, for example, losing sports games (Card and Dahl, 2011) or police shootings (Mikdash and Zaiour, 2024). Another strand of papers discuss how financial innovation influences people's criminal behaviors (Lin and Pursiainen, 2023; Huck, 2024). However, this piece of evidence mainly focuses on violent crimes, as well as on the traditional financial market innovation. For crimes fueled by the cryptocurrency market, existing papers focus on market manipulation (Griffin and Shams, 2020; Cong et al., 2023) and illegal transactions (Foley et al., 2019; Cong et al., 2025) which investigate the criminal behaviors connected to cryptocurrency trading activities. More broadly, Bian et al. (2023) and Phua et al. (2025) document the costs associated with increasing online activities, particularly those arising from identity theft and misuse of personal information. We contribute by documenting broader unintended consequences of a financial innovation on real economic activities beyond the financial sector.

Finally, our research examines the role of digital currencies as an anonymous alternative to the traditional banking system, thereby contributing to the literature on their function as shadow or substitute intermediaries for conventional financial intermediation. Whited et al. (2022), Keister and Sanches (2023), Chiu et al. (2023), and Bai et al. (2025) show the potential of Central Bank Digital Currencies (CBDC) to disintermediate banks and disrupt the traditional financial system. Berger et al. (2023) shows that the participation in cryptocurrency markets can affect the real economy by weakening traditional financial intermediation such as banks. However, existing research provides limited empirical evidence on how individuals actually use cryptocurrencies or digital currencies for monetary transactions. CBDCs largely remain at the theoretical or pilot stage without widespread adoption, while cryptocurrencies have primarily been used within the crypto ecosystem and have had limited real-world transactional impact, aside from association with illegal activities. We are the first to show that one of the primary uses of cryptocurrency is as a shadow intermediary for unbanked and low-income households. Using the installation of crypto ATMs as a shock, we provide a comprehensive look at the impact of cryptocurrency from the blockchain to the physical world.

Taken together, our findings provide the first empirical evidence on how the main street adoption of cryptocurrencies affects the financial market, households, and real economy, revealing a fundamental trade-off that policymakers must weigh before endorsing widespread adoption. Crypto ATMs are unique in that they increase public awareness and adoption of alternative assets by providing tangible, accessible entry points. By reducing participation frictions and functioning as substitutes for traditional bank branches, these ATMs replicate core financial services, such as deposit, withdrawal, and payment, outside conventional oversight. While this promotes convenience and participation, especially among the unbanked, it also heightens risks of fraud, identity theft, and illicit spillovers. Our contribution highlights how even modest reductions in access barriers can fundamentally alter the boundaries of household finance, shadow banking, and regulatory design along the financial inclusion–privacy–crime frontier.

2 Institutional Background, Data, and Empirical Strategies

2.1 The Rise of Crypto ATMs

Crypto ATMs, also known as Bitcoin ATMs or BTMs, have emerged as a significant gateway for public participation in the blockchain economy in the United States. The first crypto ATM was installed on October 29, 2013, in a coffee shop in Vancouver, Canada. Since then, the number of crypto ATMs has grown rapidly across the United States and globally. These machines offer a simple, straightforward, and accessible method of purchasing cryptocurrency, typically allowing users to transact with cash or debit cards. Our analysis focuses primarily on the rapid expansion of crypto ATMs within the United States, which has the largest crypto market around the globe.[3]

Since their introduction in 2013, the number of operational crypto ATMs surpassed 30,000 by the end of 2022. Appendix Figure A1 displays a sample photograph of a crypto

[3]Please see additional information from https://www.grandviewresearch.com/industry-analysis/crypto-atm-market-report: The crypto ATM market in North America dominated the global industry in 2023 and accounted for a share of 45.8%.

ATM for illustrative purposes. We show the total number of crypto ATMs within the United States in Appendix Figure A2, and in Appendix Table A1, we present more statistics, including the total number of zip codes and population with access to crypto ATMs annually over the past decade. In Figure 1, we present a county-level map that illustrates the number of crypto ATMs from the end of 2018 to the end of 2022, offering a visual representation of their geographic penetration and adoption over time. As of 2022, Los Angeles county has the largest number, totaling 1,141 crypto ATMs.

Crypto ATMs provide a simple, familiar on-ramp for people who are new to digital assets. By mirroring the workflow of a traditional bank ATM, they lower the learning and operational barriers that often discourage first-time users: a person can interact with a physical machine, follow step-by-step prompts, and convert crypto into local fiat cash on the spot.[4] Just as importantly, their visibility in everyday locations can spark curiosity—"what is this machine?"—and that initial exposure can motivate people to learn what cryptocurrency is and later participate more actively through other channels, including traditional centralized exchanges.

In addition, crypto ATMs can offer a privacy-preserving entry point for users who are cautious about sharing personal data. Although blockchain transactions are decentralized, many participants access the ecosystem through centralized exchanges where identity verification and compliance checks are standard, often involving facial recognition and official documentation on mobile phones. In contrast, crypto ATMs may allow certain transactions with less detailed personal information, which can feel more anonymous to users and therefore more approachable as a first interaction with crypto.[5] This can be particularly appealing to users who value personal data privacy, while also serving as a "first step" that encourages further engagement with the broader cryptocurrency market over time.

Moreover, crypto ATMs offer greater convenience of use. These machines are always installed in everyday locations, such as coffee shops, grocery stores, gas stations, and laundromats, which are often within walking distance of residential areas. Their widespread availability and 24/7 operation make it easier for users to buy or sell cryp-

[4]This is documented in recent commercial reports and government reports, such as https://pmc.ncbi.nlm.nih.gov/articles/PMC10907656/.

[5]For detailed information, please see: https://investinatmmachines.com/blog/cryptocurrency-atm-benefits-risks-rewards/. Additional information by Thomson Reuters: "More than half of the 36,000 BTMs [Crypto ATMs] in the United States do not require photo identification to conduct transactions ranging from $250 to over $1,000." See https://www.thomsonreuters.com/en-us/posts/investigation-fraud-and-risk/cryptocurrency-atms/.

tocurrency without having to adhere to traditional banking hours. Due to their relatively low installation and operating costs, crypto ATMs are increasingly accessible in rural areas. This expansion helps reduce the need for long trips to the downtown where traditional banks and financial institutions are typically located, thereby improving financial accessibility for underserved people.

The demand for crypto ATMs is substantial, as evidenced by the large number of machines currently operating across the United States. People utilize crypto ATMs for a variety of purposes. One common use is to purchase cryptocurrency as an investment. Since the market's surge in popularity around 2012, many individuals have entered the crypto space, particularly to invest in Bitcoin, with hopes of capitalizing on its rising value to generate additional income.

While crypto ATMs offer significant benefits by facilitating public access to the cryptocurrency market, they also present notable challenges—particularly in the realm of financial regulation. As mentioned above, transactions conducted through crypto ATMs are often unmonitored and lack consistent regulatory oversight, creating potential opportunities for misuse. Financial criminals may exploit these machines for illicit activities due to their relative anonymity and decentralized nature. For example, the FBI reported nearly 11,000 complaints related to cryptocurrency ATM fraud in 2023.[6] This issue is not confined to the United States; similar concerns have emerged globally, including countries such as Australia.[7]

2.2 Data Description

Crypto ATMs information. *CoinATMRadar* is a global platform that helps users locate crypto ATMs in their area or anywhere around the world, which provide the most comprehensive and detailed information about each crypto ATM. We obtain the information for each of the crypto ATMs located in the United States from its website[8], including the geographic information (longitude and latitude), installation dates, and removal dates for each of the crypto ATMs. We manually validate the information using Google Map to check the accuracy of the information. We show the total number of crypto ATMs within

[6] For details, https://nebraskaexaminer.com/2025/07/28/citing-potential-for-fraud-blue-and-red-states-pass-new-crypto-atm-laws. Other news also addresses these issues, for example, https://consumer.ftc.gov/consumer-alerts/2024/09/scammers-use-bitcoin-atms-steal-your-money.

[7] For example, https://www.afp.gov.au/news-centre/media-release/3-million-lost-cryptocurrency-atm-scams-12-months-may-be-just-tip-iceberg.

[8] Please see https://coinatmradar.com/.

the United States in the Appendix Figure A2. Figure 1 visually presents the emerging number of crypto ATMs by county, and in Appendix Table A1, we present the summary statistics on an annual basis to illustrate the growing penetration of crypto ATMs into everyday life. Table 1, Panel A presents the summary statistics of the quarterly frequency number of crypto ATMs at the county-level.

Individual App usage data. We measure cryptocurrency-related activities using a novel dataset provided by Global Wireless Solutions (GWS), which captures anonymized cell phone signal and application usage data at the zip code level from January 2019 to January 2023. Such datasets are widely utilized across industries to analyze user behavior and optimize sales performance. The data is collected via smartphone operating systems (mainly Android), which record device geolocation with timestamps at intervals of milliseconds. Location estimates are typically accurate within 20 meters and, subject to user permissions, are accessible to both open- and back-ground applications. This data provider aggregates individual and app usage data from a broad spectrum of popular applications available on major app stores, encompassing categories such as cryptocurrency, stock trading, messaging, social media, navigation, music, photography, weather, travel, health and fitness, among others. Also, the provider reports coverage for more than 0.4 million monthly active users in the United States.

While it is possible that some app usage may not be captured, due to factors such as devices being powered off, loss of reception, or relevant apps not running, the resulting measurement error can be attributed to individual user behaviors, such as the frequency with which users clear background apps. Thus, we aggregate this dataset to a low frequency, or quarterly level, to measure user's crypto app as well as stock app usage. For each individual-quarter level observation, we set a dummy that equals one if the user engages in cryptocurrency apps or stock apps, and zero otherwise. Table 1, Panel B presents the summary statistics of individual-level usage of crypto and stock-related apps. As can be seen, the average engagement rate of crypto-related apps around all observations is about 7.77%. If we only check the sample of 2022 only, then the number becomes 12.47%. This value is close to the estimated average holding of crypto assets as of 2022, which is approximately 12% to 13%.[9] This suggests that our data cover a representative sample of population in the United States.

[9]For more information, please see https://www.triple-a.io/cryptocurrency-ownership-data/cryptocurrency-ownership-united-states-2022.

Criminal incident reports. We utilize data from the National Incident-Based Reporting System (NIBRS), which provides detailed records of reported criminal incidents categorized by crime type. Each entry includes essential information such as the date and time of the incident, along with the zip codes or counties covered by the reporting agency. For the purposes of our study, we focus specifically on cyber-related offenses, including identity theft, wire fraud, impersonation, and computer invasion. These crimes are particularly relevant to the financial sector, and especially to the cryptocurrency market, in contrast to more conventional offenses such as assault, theft, or larceny. Since these police agencies began reporting identity theft cases in mid-2014, we restrict our analysis to the period from 2015 to 2022, encompassing 32 year-quarters. We present the summary statistics of such criminal behaviors in Panel C of Table 1.

Consumer reports. We obtain consumer report data from the Consumer Complaint Database maintained by the Consumer Financial Protection Bureau (CFPB), which began collecting and publishing consumer complaints in 2012. As the volume of complaints became substantial starting in 2013, we limit our sample period to the years 2013 through 2022. To measure instances of financial fraud, we focus on complaints that explicitly refer to issues such as "fraud or scam" or "unauthorized transactions," which directly indicate criminal or deceptive financial activity. In contrast, complaints related to routine inquiries, such as "closing your account" or "getting a loan" are excluded from our main analysis, as they do not reflect fraudulent behavior. Based on the categories and details reported by consumers to the CFPB, we classify complaints into three subcategories of financial fraud: *(i)* Information leakage: Cases where consumers report that their personal information, such as identity details, photographs, or credit card numbers, has been stolen or compromised. *(ii)* Suspicious transactions: Complaints involving unauthorized transactions that the consumer did not initiate or approve. *(iii)* Fraudulent debt: Instances in which consumers unexpectedly incur debt on their credit or debit cards without their consent. These three types of financial fraud reports reveal actual economic losses and represent the most prevalent forms of financial fraud in the United States in recent years. In Panel D of Table 1, we show the summary statistics. In our Appendix Table A2, we provide a detailed number for each category of consumer reports we collect from this dataset.

2.3 Identification Strategies

2.3.1 Shift-Share Instrumental Variable Approach

In this section, we outline our main identification strategy designed to estimate the causal effect of crypto ATM installations on regional financial behaviors, including cryptocurrency market participation, stock market participation, and potential increases in cybercrime and financial identity fraud. The primary challenge is to disentangle changes in ATM installations arising from firms' strategic market expansion decisions, as opposed to those driven by local demand for cryptocurrency services.

To address this, we construct a measure of county-level exposure to new crypto ATM installations that leverages exogenous variation in ATM placement across the national market. Specifically, our strategy is analogous to a Bartik (shift-share) instrument (Bartik, 1991; see also Goldsmith-Pinkham et al., 2020). The "shift" component is given by the number of crypto ATM installations originating from other counties, while the "share" reflects the pre-existing credit linkages between counties, as proxied by the flow of Small Business Administration (SBA) loans. Formally, for county j at time t, our exposure measure is constructed as follows. Let i denote the origin counties and j denote the destination counties. If banks in county i extend SBA loans to small businesses in county j, and county i experiences an increase in crypto ATM installations, then county j is more likely to subsequently see a crypto ATM installation. The intensity of this effect is weighted by the share of SBA loans that county j receives from banks in county i, relative to all SBA loans received by county j from external counties. This approach excludes lending relationships within the same or adjacent counties to mitigate the confounding effects of local demand shocks.

Let j denote the destination county, i the origin county, and t the time period. The Bartik-style instrument for county j at time t is:

$$Bartik_{jt} = \sum_{i \neq j} w_{ij,0} \cdot NumCryptoATMs_{it} \tag{1}$$

where

$$w_{ij,0} = \frac{\text{SBA loans from banks in county } i \text{ to firms in county } j \text{ at baseline}}{\sum_{k \neq j} \text{SBA loans from banks in county } k \text{ to firms in county } j \text{ at baseline}} \tag{2}$$

and ATM_{it} is the number of crypto ATMs in county i of year-quarter t. To be conservative, we exclude the adjacent counties of i when calculating the "share" in such Bartik-style instrument. In summary, our instrument for county j's exposure to crypto ATM installations is defined as the sum over all other counties i of *(i)* the number of crypto ATMs in county i of t, multiplied by *(ii)* the share of SBA loans that county j receives from county i in the baseline period. This design ensures that our measure captures exogenous shifts in ATM supply that are plausibly unrelated to contemporaneous changes in county j's unobservable demand for cryptocurrency services.

This identification strategy is based on two main assumptions: *(i)* The cross-county variation in the national expansion of crypto ATMs is driven by supply-side factors and is not systematically correlated with unobserved, time-varying demand shocks in destination counties. *(ii)* The pre-existing credit linkages, as captured by SBA loan flows, are not themselves endogenous to unmeasured determinants of local cryptocurrency demand during the sample period. We discuss these assumptions and potential threats to identification in more detail below.

First of all, because of the localized impact of crypto ATMs, the demand for cryptocurrency within a given county is unlikely to affect ATM installations in other counties, especially when those counties are not geographically adjacent. However, the presence of crypto ATMs in other counties can influence this county when the two are highly economically interconnected, given that one of the primary functions of crypto ATMs is to facilitate monetary transactions. Therefore, the existence of crypto ATMs in *non-adjacent* counties serves as a useful instrumental variable for identifying local increases in the number of crypto ATMs.

Second, the pre-existing credit linkages is persistent. To test the hypothesis, we run a regression of the pre-existed linkage as captured by the lagged value of "shares" on that of the current linkage. We present the regression results in our Appendix Table A3. Our results show that the persistence of this linkage is around 85%. This further validates that our linkage is persistent and exogenous across time. Additionally, we conduct a pre-trend test. We predict a set of macroeconomic factors with the instrumental variable leading by several quarters. The results are reported in the Appendix Table A4, and we find no correlation between the leading instrumental variables as well as these macroeconomic variables.

We then run the regression as follows to get the instrumented number of crypto ATMs per county:

$$NumCryptoATMs_{ct} = \beta Bartik_{ct} + \textit{Year-Quarter FE} + \textit{County FE} + \varepsilon_{ct} \tag{3}$$

in which $NumCryptoATMs_{ct}$ is the total number of crypto ATMs of county c in year-quarter t. $Bartik_{ct}$ is our Bartik-style instrumental variable. We include a full set of time fixed effects as well as county-level fixed effects in this regression. This is the first stage regression of our instrumental variable approach, which is recorded in our Appendix Table A5. The reported F statistic is 85, indicating that the Bartik-style instrument employed in this analysis does not suffer from weak instrument problems. We use the predicted number of crypto ATMs using Equation 4 as the instrumented number of crypto ATMs per county. The predicted number of crypto ATMs is denoted as $Num\widehat{Crypto}ATMs$.

For robustness checks, we provide an alternative approach to construct our Shift-Share instrumental variable: For each county, we exclude the highest connected county and calculate the weighted average number of crypto ATMs based on the remaining counties. The first stage regression of this alternative instrument is reported in the Appendix Table A6.

Alternative instrumental variable. As a robustness check, we introduce an alternative instrumental variable. The instrument is defined as street density measured in 2011 multiplied by the Bitcoin price at the close of each year-quarter. The corresponding first-stage regression is given by:

$$NumCryptoATMs_{ct} = \beta StreetDensity2011_{c} \times BitcoinPrice_{t} + \textit{Year-Quarter FE} + \textit{County FE} + \varepsilon_{ct} \tag{4}$$

The first stage regression is reported in the Appendix Table A7. The F-statistic of 666 demonstrates that the instrument is sufficiently strong for explaining the number of crypto ATMs, thereby alleviating concerns regarding weak instruments.

2.3.2 Difference-in-Differences Approach

Another identification strategy we employ is the difference-in-differences (DiD) approach. For variables that cannot be disaggregated to the county level or more granular geographic units, such as police agency-level data or individual-level app usage, we implement a DiD estimation. This method is particularly suitable given that the installation of crypto ATMs generates a concentrated and localized shock, allowing us to capture dynamic treatment effects within narrowly defined areas. The DiD event is defined as the installation of the first crypto ATM within the specified geographic region. In our context, the region could be defined by zip code boundaries, census blocks, or jurisdictional areas of individual police agencies, based on the data quality we obtained for each of the variables. Specifically, we estimate the following regression:

$$Outcome_{it} = \beta PostCryptoATM_{it} + County \times Year\text{-}Quarter\ FE + Region\ FE + Control + \varepsilon_{it} \quad (5)$$

where $PostCryptoATM_{it}$ is a difference-in-differences dummy equal to one if time t occurs after the first crypto ATM installation in region i, and zero otherwise. We include county times year-quarter fixed effects, region fixed effects, as well as a set of macroeconomic control variables in this regression.[10] To test the parallel trend before crypto ATMs' installation, we then apply the following event-study framework:

$$Outcome_{it} = \sum_{T} \beta_T T_{it} + County \times Year\text{-}Quarter\ FE + Region\ FE + Control + \varepsilon_{it} \quad (6)$$

in which T_{it} is a set of dummies indicating quarters before or since the first crypto ATM installed in a region.

3 Financial Inclusion and Participation

Our first set of empirical evidence on the influence of the cryptocurrency market on the real economy focuses on individuals' engagement with financial markets. As highlighted in previous theoretical literature such as Philippon (2019), new financial technologies have the potential to enhance financial inclusion. In this section, we provide empirical evidence to support and extend these theoretical insights. We employ multiple identification strategies to provide robust evidence that the installation of crypto ATMs leads to increased regional participation in financial market activities.

[10] For identification at the police agency level, where jurisdictions may span multiple counties, we only include year-quarter fixed effects in our regressions. The details are discussed in detail in the relevant sections.

3.1 Instrumental Variable Estimation

In this section, we use an instrumental variable approach to test how the installation of crypto ATMs can influence regional financial market engagement. As crypto ATMs are used for cryptocurrency trading, we first focus on the engagement in the cryptocurrency market, following the identification strategy as demonstrated in Section 2.3. We run the following regression:

$$\begin{aligned} EngageCrypto_{czit} =& \beta Num\widehat{CryptoA}TMs_{ct} + Year\text{-}Quarter\ FE \\ &+ County\ FE + Control + \varepsilon_{czit} \end{aligned} \tag{7}$$

in which $EngageCrypto_{czit}$ is a dummy variable to measure engagement in the cryptocurrency market, which equals one if individual i in zip code z of county c uses crypto-related apps during year-quarter t and zero otherwise. $Num\widehat{CryptoA}TMs_{ct}$ is the Bartik-style instrumented number of crypto ATMs of county c in year-quarter t. In our baseline model, we include a full set of year-quarter fixed effects as well as county-level fixed effects, as well as control variables of county-level macroeconomic indexes including population, wage, and total number of employment. We multiply our regression coefficient by 100 for a clearer presentation.

Our main sample period spans from the first quarter of 2019 to the fourth quarter of 2022. Although the first crypto ATM in the United States was installed in 2014, our dataset captures the core and major period during which crypto ATMs experienced rapid expansion. As illustrated in Figure 1 and summarized in Appendix Table A1, there were fewer than 2,000 crypto ATMs across the United States at the beginning of our sample, covering approximately 1,500 zip codes. This suggests that, at the start of our observation period, a substantial portion of the population resided in areas without access to crypto ATMs, offering a useful baseline for comparison and serving as an informative "prior" in our analysis. By the end of 2022, the number of crypto ATMs had surged to over 32,000, with nearly 9,600 zip codes hosting at least one ATM. This staggered and sharp growth in crypto ATM installations during our sample period help us identify the causal relationship between crypto ATM proliferation and regional economic activity.

Table 2 presents our Bartik-style instrumental variable estimates, which help identify the causal effect of crypto ATM installations on individuals' participation in the cryptocurrency market. We estimate Equation 7, incorporating county-level fixed effects and time fixed effects, without or with a set of macroeconomic control variables (Columns 1 and 2). Our baseline regression reveals a positive causal relationship between the number of crypto ATMs installed and regional individual engagement in the cryptocurrency market. According to our estimates, the installation of one additional crypto ATM in a county increases the probability of individual cryptocurrency engagement by 0.12%, which translates to approximately 102 new cryptocurrency holders per county on average. As of the end of 2022, the average number of crypto ATMs per county was 10, implying that crypto ATM installations are associated with roughly 1,020 new cryptocurrency holders per county. This effect size is both substantial and plausible, especially when considered alongside the statistic that 13.7% of adults held crypto assets by the end of 2022.[11]

We assess the robustness of our main empirical findings using alternative model specifications. First, we additionally control the state fixed effects times bitcoin price to mitigate concerns about event timing and crypto market cycles (Column 3). Our conclusion remains under such a specification. Second, we incorporate more granular geographical fixed effects, specifically, zip code fixed effects, as well as the state fixed effects times bitcoin price (Columns 4). The results remain robust and the regression coefficients show minimal change compared to our baseline estimates, indicating that our findings are not driven by broader regional variation. Next, we include individual-level fixed effects and state fixed effects times the price of bitcoin (Column 5), representing the most strict specification in our analysis. Under this more demanding empirical specification, the results remain statistically significant, with only small changes in the estimated coefficients relative to the baseline model. Together, our results provide clear and significant evidence of a causal effect: the installation of crypto ATMs increases regional engagement in the cryptocurrency market.

To further justify that our Shift-Share Instrument is exogenous, we conduct our second-stage regression of Equation 7 on the subsample with no crypto ATMs installed in a given county-year-quarter observation. We report the regression results in our Appendix Table A8. We find almost no significant correlation between the instrumented number of crypto ATMs as well as individuals' engagement in the crypto market. This finding further suggests that there is almost *no* correlation between the variation of instrumented number of crypto ATMs and regional demand for cryptocurrency. Moreover, we provide another estimation based on alternative Shift-Share instrumental variable which excludes highest connected counties to avoid that our results are driven by some major cities. The results

[11] The estimated number of crypto asset holder in the United States is 46 million, about 13.7% of America's total population. See https://www.triple-a.io/cryptocurrency-ownership-data/cryptocurrency-ownership-united-states-2022 for more details.

are reported in the Appendix Table A9, which shows that our results remain.

We additionally provide an alternative estimation using a different instrumental variable, defined as the interaction between street density in 2011 and the bitcoin price, as discussed in the second part of Section 2.3.1. The results are reported in Appendix Table A10. Our findings remain robust under this specification.

Moreover, we present the OLS regression coefficients, using the total number of crypto ATMs per county as the independent variable in Appendix Table A11. As shown, the coefficients are consistently positive across various specifications. Specifically, the estimates remain positive when controlling for county and time fixed effects (Column 1), and when adding macroeconomic control variables (Column 2). The results also hold when additionally controlling for state-level fixed effects times bitcoin price (Column 3). Furthermore, the coefficients remain robust when zip code fixed effects or individual fixed effects are included (Column 4 and Column 5), indicating that the observed relationship is not driven by basic geographical or demographic factors that may influence individual behavior. Our OLS specification presents a positive correlation between the number of crypto ATMs as well as regional cryptocurrency market engagement.

The extensive margin. Lastly, we provide additional results on the extensive margin. We replace the dependent variable in the empirical specification of Table 2 with the minutes of engagement in crypto-related apps. The corresponding results are reported in Appendix Table A12. On average, the installation of one additional crypto ATM is associated with an increase of 0.3720 minutes of engagement per person in a region. The magnitude of this effect is economically meaningful. For example, in a county with 100,000 residents and at least 10 crypto ATMs, the presence of these ATMs implies roughly 6,200 additional hours spent on crypto-related apps per quarter.

3.2 Individual-Level Quasi-Natural Experimental Evidence

To supplement our identification, we also implement a difference-in-differences approach to estimate the impact of crypto ATMs on financial engagement. Specifically, we examine the effect of the first crypto ATM installation within an individual's neighborhood, that is, the zip code where she/he lives. By leveraging the staggered roll-out of crypto ATMs across regions, we are able to identify the causal effect of first-time exposure to crypto ATMs on individuals' decisions to engage in the cryptocurrency market.

We design our empirical specification as follows:

$$\begin{aligned} EngageCrypto_{czit} =& \beta PostCryptoATM_{it} + County \times Year\text{-}Quarter\ FE \\ &+ Individual\ FE + Control + \varepsilon_{czit} \end{aligned} \tag{8}$$

in which $EngageCrypto_{czit}$ is a dummy variable to measure the engagement in cryptocurrency market, which equals one if individual i in zip code z of county c uses crypto-related apps during year-quarter t and zero otherwise. $PostCryptoATM_{it}$ is the difference-in-differences dummy variable equals to one if individual's living zip code z installed its first crypto ATMs before or during year-quarter t and zero otherwise. To be conservative, we include a full-set of county and year-quarter joint fixed effects as well as individual fixed effects in our regression in our baseline specification. The macroeconomic control variables include zip code level income as well as population.

Table 3 presents the results. In Panel A, we present our baseline estimates focusing exclusively on individuals residing in zip codes that had no crypto ATMs at the beginning of the sample period. This allows us to estimate the quasi-natural experimental effects on a sample that excludes always-treated individuals. We begin by estimating Equation 7 with a full set of zip code and time fixed effects (Column 1), and then with the addition of macroeconomic control variables (Column 2). Further specifications include models with individual fixed effects (Column 3), individual fixed effects combined with state-by-time fixed effects (Column 4), and individual fixed effects combined with county-by-time fixed effects (Column 5). Across all specifications, the estimated coefficients remain stable in both economic magnitude and statistical significance. Based on our baseline estimates, we find that first-time exposure to a crypto ATM increases the probability of individual engagement in the cryptocurrency market by 0.67%.

We further introduce an alternative empirical specification by incorporating a different control group within our quasi-natural experimental framework. As highlighted in previous empirical economic research (for example, the difference-in-differences design of Dooley and Gallagher, 2024), including an early-treated group as part of the control sample can help mitigate potential location-selection bias of the crypto ATMs. Panel B of Table 3 presents the corresponding results. Under this specification, we include individuals residing in zip codes where the first crypto ATMs were installed prior to 2017 as part of the control group. As shown, our findings remain robust relative to the baseline results in Panel A, both in terms of economic magnitude and statistical significance.

Based on the two empirical specifications, we use an event-study approach to examine the dynamic impact of crypto ATM installation on individuals' decisions to engage in the cryptocurrency market. Specifically, we replace the treatment indicator in Equation 8 with a series of dummy variables representing quarters before and after the initial exposure to a crypto ATM. We use the quarter immediately preceding the first installation as the reference period. Figure 2 presents the event-study results corresponding to our baseline specification. In our Appendix Figure A3, we provide another event-study estimation which includes the early-installation always-treated group as the control. In Appendix Figure A4, we use a stacked difference-in-differences strategy to estimate the coefficients. Both estimations include macroeconomic control variables, along with a full set of individual and time fixed effects, state-by-time joint fixed effects, or county-by-time joint fixed effects (our baseline model). The estimated coefficients reveal no significant pre-treatment trends, supporting the validity of our identification. The probability of participating in the cryptocurrency market increases by approximately 2.5% within one year following the first crypto ATM installation.

3.3 Participation in the Stock Market

We extend our analysis for the effect of crypto ATMs' installation on cryptocurrency market participation to study such effects on individuals' stock market engagement. To facilitate this analysis, we collect app usage data on stock-trading related apps, such as *Robinhood* and *Yahoo Finance*, and the results are reported in Table 4.

In Panel A, we use a similar empirical specification as Equation 7 but changing the dependent variable in this regression to the dummy for stock-trading app engagement. Our results show that the installation of crypto ATMs has a positive impact on the engagement on the stock market. The regression coefficients, however, are slightly less statistically significant compared to our conclusions obtained from the cryptocurrency trading apps. Panel B documents a similar conclusion by using the difference-in-differences approach as Equation 8: Following the installation of crypto ATMs near their residence, individuals become more likely to engage in the stock market. Figure 3 shows the event-study dynamics based on the specification of Panel B, Table 4. With different sets of fixed effects, we obtain robust and significant results, indicating that the installation of crypto ATMs increases individuals' engagement in the stock market. Our results suggest that crypto ATMs not only increase regional participation in the cryptocurrency market, but also stimulate engagement in traditional financial markets such as the equity market.

3.4 Heterogeneous Effects by Crypto Apps

We end our discussion about financial market engagement by studying how people engage in the cryptocurrency market. Based on our baseline empirical specification we described in Equation 7, we analyze which kind of cryptocurrency-related apps are influenced by the installation of crypto ATMs. Accordingly, we revise Equation 7 by replacing its dependent variables with dummy variables that denote usage across different categories of cryptocurrency-related applications. We classify cryptocurrency related apps into four categories: Decentralized payment and/or credit services based on the blockchain ecosystem, mainly the *Crypto.Com* app; the apps for centralized cryptocurrency exchange, mainly including *Coinbase* and *Binance*; the cryptocurrency-related information and news apps, mainly *CoinMarketCap*; and other small cryptocurrency platforms.

The estimated coefficients are presented in our Appendix Table A13. An interesting finding is that the installation of crypto ATMs is much more significantly associated with increased engagement in apps offering a broad range of cryptocurrency-related services, such as credit cards, NFTs, DeFi, and others, exemplified by platforms like *Crypto.com*, compared to the participation in centralized exchange markets, despite these centralized platforms exhibiting higher overall engagement (as reflected in the mean value of the dependent variable). One plausible explanation for this heterogeneity is that multi-service apps like *Crypto.com* are more compatible with the functionalities provided by crypto ATMs, for example purchasing goods for everyday consumption.

As discussed in Section 2.1, individuals primarily use crypto ATMs for monetary transactions rather than investment purposes. In support of this interpretation, we observe a weaker positive correlation between the presence of crypto ATMs and engagement with centralized cryptocurrency exchanges, both in terms of economic magnitude and statistical significance. Prior research on blockchain activity indicates that users of centralized exchanges are predominantly driven by investment purposes (Makarov and Schoar, 2025). Therefore, the observed heterogeneous effects may indicate that the primary use of crypto ATMs lies in financial services beyond investment, such as everyday monetary transactions. Taken together, our findings lend empirical support to anecdotal evidence from the media suggesting that crypto ATMs are gradually contributing to the normalization of cryptocurrency as an alternative form of fiat money.

Additionally, we find a positive but statistically not so significant correlation between the installation of crypto ATMs and the usage of crypto-related information apps. Lastly, the effects on smaller cryptocurrency-related apps are statistically significant. These apps tend to be less regulated, suggesting that some less-sophisticated cryptocurrency users may engage with unregulated services offered through such platforms. Notably, some of these apps may be fraudulent, raising concerns about user vulnerability and the potential risks associated with increased access to cryptocurrency through ATMs.

3.5 Startup Formation as a Downstream Effect

Beyond household financial engagement, easier access to crypto may influence local entrepreneurial activity. Crypto ATMs lower entry costs into the digital-asset ecosystem and broaden participation in speculative and transactional uses of crypto. To the extent that these frictions previously constrained innovative startups in payments, blockchain services, or related technologies, ATM expansion could spur new firm formation.

We examine county-level startup entry rates, focusing on industries more likely to be affected by crypto adoption. We proxy startup formation using two measures: the total number of small business loan applications per 1,000 capita, and the amount of business loans (in U.S. dollars) per capita. Using our shift–share IV design, we find that one additional crypto ATM is associated with a 0.0004 increase in new firm registrations per 1,000 residents, and this number is much more significant in the pre-COVID period, which is 0.003 (Panel A of Table 5). Additionally, one more installed crypto ATMs is associated with a 432 U.S. dollars increase in regional small business loans. This value is also more significant within the pre-COVID sample, which is about 1,527 (Panel B of Table 5). These effects are economically meaningful relative to baseline entry rates, though smaller in magnitude than the household financial-engagement effects documented above. While these results should be interpreted cautiously, they suggest that the effects of reducing access and privacy frictions extend beyond households to local entrepreneurial ecosystems. This finding connects to the broader household-finance literature showing how participation costs shape not only asset ownership but also real economic activity, such as small business formation and employment (Adelino et al., 2015, 2017).

3.6 Robustness Checks

We conduct a series of additional robustness and falsification exercises to assess the validity of our identification strategy. First, we perform balance tests showing that treated and control individuals are comparable along observable demographic characteristics, baseline financial activity, and pre-treatment transaction behavior prior to the installation of the first nearby crypto ATM. We also implement placebo outcome tests using variables that should not be affected by crypto ATM access, including non-financial consumption categories, unrelated digital payment usage, and pre-existing trends in bank account balances and credit card spending. Across these placebo outcomes, we find no statistically significant effects around ATM installation.

Second, we consider alternative shocks as falsification instruments. Specifically, we replace the timing of crypto ATM installation with (i) the opening of unrelated retail locations, (ii) placebo installation dates randomly reassigned within the same geographic area, and (iii) changes in local infrastructure unrelated to financial services. These alternative shocks do not predict any changes in cryptocurrency usage, equity market participation, or other financial outcomes, indicating that our results are not driven by generic local economic activity or coincident shocks.

Finally, we verify that the instrument does not predict crypto-specific outcomes in the pre-treatment period. We find no evidence that future crypto ATM installations are correlated with pre-existing trends in cryptocurrency transactions, crypto wallet creation, or digital asset holdings. Appendix A4 reports several of these pre-trend and placebo tests for aggregate macroeconomic and financial variables.[12]

4 Criminal Behavior and Socioeconomic Implications

We analyze the rise in financial crime through the lens of the economic theory of rational criminal choice. We hypothesize that the introduction of crypto ATMs, a technology that enhances the anonymity of financial transactions, lowers the expected cost of committing financial crimes by reducing the probability of apprehension. We test the prediction that a reduction in this expected cost leads to an increase in the equilibrium supply of such crimes.

[12] Additional balance tables, placebo outcome results, alternative-shock falsification tests, and pre-treatment predictability analyses for crypto-specific outcomes are available upon request. All results are consistent with the baseline findings.

Despite the benefit brought by crypto ATMs, we continue our empirical analysis to study the negative impact of crypto ATMs on the financial market. In this section, we provide evidence on its impact on cybercriminal behaviors.

4.1 Criminal Incidents Reports for Cybercriminals

The first set of empirical evidence we provide on how crypto ATMs or the cryptocurrency market foster cybercriminals is by analyzing the criminal incidents reported by each police agency. As the area of each policy agency covered ranges from several zip codes to several counties, this data structure restricts us from using the Bartik-style instrument in our analysis. Hence, we use a difference-in-differences approach to study such impacts, and the regression specification is documented below:

$$\begin{aligned} CyberCrimeRate_{pt} = &\beta PostCryptoATM_{pt} + Year\text{-}Quarter\ FE \\ &+ Police\ Agency\ FE + Control + \varepsilon_{pt} \end{aligned} \tag{9}$$

in which $CyberCrimeRate_{pt}$ is the cybercriminal rate, calculated by the total number of cybercriminals per 1,000 capita, reported by police agency p at year-quarter t. $PostCryptoATM_{pt}$ is a dummy that equals one after the first installation of crypto ATMs in the areas covered by police-agency p and zero otherwise. We include a full set of controls, including the income, total population, as well as the number of employments. We also include a full set of time fixed effects as well as police agency fixed effects in the regression.

Since the National Incident-Based Reporting System began recording identity theft incidents in mid-2014, our sample period spans from the first quarter of 2015 to the last quarter of 2022, covering 32 year-quarters. To ensure the validity of our identification strategy, we exclude police agencies that had at least one crypto ATM installed before the beginning of the treatment period (the always-treated group). These police agencies represent a relatively small sample, and most of them installed crypto ATMs in 2014.

Table 6 presents our findings. Panel A reports the estimated regression coefficients for cybercrimes related to identity theft. Among various categories of cybercrime, identity theft appears most closely linked to financial markets, particularly within the unregulated cryptocurrency market. Our baseline specification (Column 1) indicates that the installation of crypto ATMs leads to an increase of 0.019 identity theft incidents per 1,000 capita. These results remain robust across several alternative specifications: when including a state-level linear trend (Column 2), when including state and time joint fixed effects

(Column 3), and when further controlling for police agency-level linear trends (Column 4).

Figure 4 visually illustrates the dynamic effects of crypto ATM installation by estimating Equation 9 with a series of dummy variables that represent quarters relative to the installation date. The event-study extension of Panel A reinforces our identification strategy, showing no significant pre-treatment trends and a persistent rise in identity theft rates for up to three years following the installation of crypto ATMs. In our Appendix Figure A6, we present the event-study estimator proposed by Callaway and Sant'Anna (2021) adjusted by heterogeneous treatment effects. Our results remain under the new specification.

In Panel B of Table 6, we examine the impact of crypto ATM installations on other types of cybercriminal activity. These behaviors, such as online gambling, welfare fraud, and similar offenses, are generally less connected to financial markets particularly the cryptocurrency market. Unlike identity theft, these categories show insignificant associations with crypto ATM proliferation.

4.2 Consumer Reports for Financial Fraud

The preceding discussion on crimes associated with crypto ATMs has primarily focused on the behavior of perpetrators and criminals, specifically, the number of illicit activities facilitated by cryptocurrency. In this section, we extend the analysis by examining how crypto ATMs contribute to financial crimes from the perspective of victims, using data from consumer complaint reports. This analysis provides a more comprehensive understanding of the disruptions to the financial market resulting from the rapid surge of crypto ATMs.

We first perform a county-level analysis. Based on our previous instrumental variable approach, we estimate the regression as:

$$\begin{aligned} FinFraudRate_{ct} =& \beta Num\widehat{CryptoA}TMs_{ct} + \textit{Year-Quarter FE} \\ &+ \textit{County FE} + \textit{Control} + \varepsilon_{ct} \end{aligned} \tag{10}$$

in which $FinFraudRate_{ct}$ is the financial fraud report rate of county c in year-quarter t. This rate is calculated by the total number of financial fraud reports aggregated to county-level per 1,000 capita, and our sample for financial fraud starts at the beginning of 2019 and ends at the last quarter of 2022. We construct three categories of such dependent variables based on the issues reported by the consumers, including information leakage, suspicious transaction, and fraudulent debt. Panel A in Table 7 shows our estimated results. We find positive and statistically significant correlations between the instrumented number of crypto ATMs as well as the financial fraud report rates across each of the three categories. Our results remain robust if we additionally control for state fixed effects times the bitcoin price, which is reported in our Appendix Table A14. Moreover, we use an alternative instrumental variable constructed without the highest connected counties to avoid that our results are driven by some major cities. Our results remain robust, as reported in the Appendix Table A15. We also present an alternative estimation using a different instrumental variable, defined as the interaction between street density and the bitcoin price. The results, reported in Appendix Table A16, confirm that our conclusions remain robust under this specification. Additionally, we provide the OLS estimation in the Appendix Table A17. We also estimate the results on all financial fraud reports, which are reported in Panel A of the Appendix Table A18,

Then, we add another identification based on the regional dynamic of crypto ATMs' installation within a zip code, as the consumer reports dataset allows us to aggregate our dependent variable to the zip code level. The difference-in-differences estimation is as follows:

$$\begin{aligned} FinFraudRate_{czt} = & \beta PostCryptoATM_{zt} + County \times Year\text{-}Quarter\ FE \\ & + Zip\ Code\ FE + Control + \varepsilon_{ct} \end{aligned} \tag{11}$$

in which $FinFraudRate_{ct}$ is calculated by the total number of financial fraud reports aggregated to the county-level per 1,000 capita for zip code z in year-quarter t. Panel B of Table 7 presents the results. Consistent with our instrumental variable estimation, we obtain a significant positive correlation between the introduction of crypto ATMs and the regional financial fraud reports. The estimated results for all financial fraud reports are reported in Panel B of the Appendix Table A18.

We further present the event-study estimation based on Equation 11, and the corresponding regression coefficients are presented in Figure 5. Notably, we find no evidence of a pre-trend in financial fraud reports prior to the introduction of crypto ATMs within a given zip code. Following the installation of crypto ATMs, the volume of fraud reports increases consistently, showing economically and statistically significant positive coefficients. These findings from consumer reports align closely with patterns observed in criminal incident reported by police agencies. We conduct such a procedure on all financial fraud reports, which is reported in Appendix Figure A7. Additionally, we provide two alternative specifications. The first step involves conducting our event study on zip codes that eventually host at least one crypto ATM, while excluding those that are never treated. This approach helps mitigate potential location selection bias. The corresponding results are presented in Appendix Figure A8 and Appendix Figure A9, and our findings remain robust under this specification. Second, we supplement our analysis using the Callaway and Sant'Anna (2021) event-study estimators to adjust for heterogeneous treatment effects. The results, presented in Appendix Figure A10 and Appendix Figure A11, indicate the robustness of our findings under this alternative specification.

Lastly, we extend our analysis to additional categories of consumer reports that relate to irregular financial issues, which may not constitute clear indicators of criminal activity. These variables can be another estimation for increasing the level of participation in the financial market. These reports are grouped into three distinct categories: incorrect information, incorrect operation, and other miscellaneous issues. We replicate the analytical framework used in Table 7 for these categories, with the corresponding results presented in Appendix Table A19. Overall, we observe a positive causal relationship between the presence of crypto ATMs and the incidence of irregular financial reports. However, the estimated effects are comparatively weaker in terms of both statistical significance and economic magnitude.

4.3 Disruption in Different Financial Industries

In this section, we extend the analysis presented in Section 4.2 by examining how specific financial sectors are affected by the introduction of crypto ATMs. Previously, we categorized financial fraud cases based on the nature of the issues described in consumer reports. Here, we reclassify these reports according to the firms targeted by consumer complaints, allowing us to assess the sectoral impact of crypto ATM installations with more precision.

Panel A of Table 8 presents the estimated impacts derived from our baseline model, as specified in Equation 10. Across all three categories of financial firms offering traditional services (mainly banks, reported in Column 1), investment and asset management firms (Column 2), and credit card companies (Column 3), the regression coefficients are positive. Among these, the coefficient associated with banks and other traditional financial service providers is the largest, indicating that core monetary services are most significantly disrupted by the emergence of the unregulated cryptocurrency market. This might be because logging into and engaging in the less-regulated cryptocurrency website requires people's bank account, or other bank transactions associated with the crypto ATMs.

Moreover, Column 4 indicates that FinTech firms are also affected by the presence of crypto ATMs. Although the volume of consumer complaints directed at financial technology companies collected by us is relatively small, we still observe a statistically significant causal relationship between the installation of crypto ATMs and the rise in financial fraud reports associated with these firms. Given that FinTech companies often facilitate online payments and monetary transactions, their services may be closely linked to cryptocurrency activity. Lastly, Column 5 shows a positive relationship between crypto ATMs and complaints involving credit scoring firms. Majority of the reports highlight credit-scoring issues arising from financial fraud, suggesting that the proliferation of crypto ATMs could ultimately undermine social trust and credit. We additionally provide the difference-in-differences estimation in Panel B of Table 8, using the same strategy as Equation 11. We obtain a similar conclusion if we follow such an identification strategy.

Taken together, the heterogeneous effects across firm types reveal important economic implications: the cryptocurrency market not only introduces regulatory complexities for digital and technology-oriented firms, but also disrupts traditional financial institutions such as banks. These findings suggest that the adverse impacts of the unregulated cryptocurrency ecosystem may spill over into broader segments of the *traditional* financial sector.

4.4 Illicit-use Spillovers: Drugs and Firearms

Beyond the direct impact on financial frauds and crimes, Crypto ATMs could have broader socioeconomic effects, especially those involving overdose caused deaths and weapon law violations. The core feature of ATMs — immediate cash-to-crypto conversion with limited KYC — can plausibly reduce frictions for purchases of drugs and firearms, which are both commodities frequently cited in law-enforcement reports as being transacted via cryptocurrency channels. Therefore, we examine whether the geographic diffusion of ATMs is associated with downstream spillovers into these markets.

Empirically, we document suggestive increases in drug-overdose deaths and firearm-related incidents following local ATM expansion. Both effects are smaller in magnitude and less precisely estimated than the crime results presented above, and we caution that they should be interpreted as exploratory. Nonetheless, the consistent positive signs across drug- and gun-related outcomes reinforce the interpretation of crypto ATMs as a broader privacy/liquidity shock whose consequences extend beyond narrowly defined finance.

We stress that these results are not the primary contribution of the paper, but rather highlight a potential externality margin that complements our core findings on financial fraud. The evidence is consistent with a general trade-off: while lower transaction frictions expand access and participation, they also open channels that can be exploited in illicit offline markets. This interpretation links directly back to the inclusion–crime frontier that underpins our welfare discussion.

Overdose caused deaths. We first investigate drug-related issues, as Foley et al. (2019) point out that cryptocurrency transactions have primarily served illegal purposes such as purchasing drugs. We test this hypothesis by analyzing overdose-related deaths using a county-level instrumental variable approach, as specified in Equation 10, substituting the dependent variable with the measure of drug-induced fatalities. We proxy overdose-related deaths using the total number of drug-abuse-induced fatalities per 1,000 capita. The results, presented in Panel A of Table 9, suggest that the installation of one additional crypto ATM is associated with an increase of 0.0015 overdose deaths per 1,000 capita per quarter. This finding remains robust across three distinct subsamples: the large-county sample, the pre-COVID sample, and the large-county pre-COVID sample. As a placebo test, we examine alcohol-related death rates and find no significant association.

Gunshots. Lastly, we employ a difference-in-differences estimation using block-level gunshot incident data from Minneapolis to examine the impact of crypto ATM installations on regional weapon-related violations. The results, reported in Panel B of Table 9, indicate that following the installation of crypto ATMs, the number of gunshot incidents increased by an average of 0.81 per block per year-quarter. The even-study extension of such results validates the identification of our conclusion, which is presented in Appendix Figure A12.

5 Heterogeneity, Welfare, and Policy

5.1 Heterogeneity and Economic Mechanisms

Heterogeneity by different level of accessibility to traditional banks. From our previous discussion, we present strong and compelling evidence that crypto ATMs are influencing the economy by expanding services that closely resemble those of traditional banking systems. In Section 3.4, we show the heterogeneity between crypto-related applications and find that the installation of crypto ATMs leads to a more pronounced and statistically significant increase in the usage of multifunctional crypto apps, such as *Crypto.com*, which offers crypto-enabled credit cards and cash withdrawal services. Furthermore, Section 4.3 shows that traditional financial industries are adversely affected by the proliferation of crypto ATMs. Building on these findings, this section provides additional evidence on the mechanisms: crypto ATMs are improving regional financial engagement by providing similar functionalities as the banking system.

We test such channels by studying the different treatment effects among regions with different levels of access to the banking system. Based on the county-level instrumental variable approach, we construct two measures: *(i)* the standardized number of banks per capita, and *(ii)* a binary indicator denoting whether a region with 1,000 residents has more than 1 bank (approximately the median value across all counties). These proxies are then interacted with both the raw and instrumented counts of crypto ATMs in the baseline regressions specified in Equation 7 and Equation 10.

Our IV estimated heterogeneous effects are reported in Table 10, while the OLS specification is shown in Appendix Table A20. The coefficients for the number of crypto ATMs are not reported in the table as they do not capture the heterogeneous effects of interest. Panel A reports the interaction effects on individual engagement in the cryptocurrency market. We find that in regions with greater access to traditional banking, the positive influence of crypto ATM installations on financial market participation is significantly attenuated. Such effects exist across three different measures for cryptocurrency market engagement: all cryptocurrency apps, the *Crypto.com*, or the centralized cryptocurrency exchange apps. We present the results visually in the Appendix Figure A13. The outcome variable is the residual of the dummy indicating using *Crypto.com* app after subtracting the estimated coefficient of county-level and year-quarter fixed effects. The independent variable is that of the (instrumented) number of crypto ATMs per county. One observes that the installation of crypto ATMs has larger effects within the region with limited access to the banking system.

We additionally provide another estimation for our mechanism based on the DiD setting as Table 3. In Appendix Table A21, we interact with the DiD dummy with variables that proxy the accessibility to banks estimated before our sample starts. In Panel A, the variable represents the total number of banks within a given zip code. In Panel B, it is a binary indicator equal to one if at least one bank is present in the zip code. Based on such a specification, we can examine whether individuals living near banks exhibit different behavioral responses to the installation of crypto ATMs compared to those residing in areas without nearby banking access. The estimated heterogeneity under this specification aligns with our main findings: the presence of banks significantly dampened the effect of crypto ATM installations on individual participation in the cryptocurrency market.

A similar pattern emerges in the context of financial fraud. In Panel B of Table 10 and Appendix Table A20, we show that regions with higher bank accessibility exhibit a lower susceptibility to crypto ATM–related financial criminal behaviors, as reflected by the consumer reports about information leakage, suspicious transactions, or fraudulent debt on their credit cards. These findings suggest that traditional banking infrastructure may serve as a buffer against some of the disruptive effects introduced by crypto ATMs. Again, we test this heterogeneity with our DiD setting as shown in Panel B of Table 7. In Appendix Table A22, we show that crypto ATMs' impact on regional financial fraud reports is attenuated by the existence of a traditional banking system.

Banks and the installation of crypto ATMs. Building on our discussion of heterogeneity by bank presence, We additionally examine the factors that determine where crypto ATM firms choose to install their machines. We ask the following question: Does the number of banks influence the decision of crypto ATM firms to install such machines? To explore this, we re-sample our dataset to an annual frequency[13] and estimate the number of new crypto ATMs installed in each county as a function of the one-year lagged number of bank closures and openings. We run the following regression:

$$\begin{aligned} NumNewCryptoATM_{ct} =& \beta_1 NumBankClose_{ct-1} + \beta_2 NumBankOpen_{ct-1} \\ &+ Control + State \times Year\ FE + County\ FE + \varepsilon_{ct} \end{aligned} \tag{12}$$

[13]This adjustment reflects the fact that bank branch openings and closures are recorded annually.

in which $NumNewCryptoATM_{ct}$ is the total number of new crypto ATMs installed in county c in year t. $NumBankClose_{ct-1}$ and $NumBankOpen_{ct-1}$ represents the one-year lagged number of bank branch closure or opening. We include state and year joint fixed effects as well as county fixed effects in our regression.

The results, presented in Table 11, reveal that crypto ATMs are negatively associated with the number of banks existing in the county. Each bank branch closure is associated with approximately 1 additional crypto ATMs installed in the county, and there are altogether 24,382 bank branches closed during our sample period. However, the number of newly opened bank branches does not have a statistically significant effect on predicting crypto ATM installations. There are also a relatively small number of bank branch openings in our sample, totaling 9,363 cases. Our results suggest that the crypto ATM firms design and install crypto ATMs as shadow intermediaries for unbanked individuals.[14]

To further validate these findings, we conduct a series of additional tests. First, we show a pre-trend analysis. Appendix Table A23 extends the analysis by incorporating lagged and lead values of bank closures and openings to predict the number of new crypto ATMs installed in a given year, and in Figure 6, we present the results visually. We find that bank closures from one year earlier and the current year are positively associated with new crypto ATM installations. Future bank closures, ranging from one to three years ahead, exhibit no correlation with the current crypto ATM deployment, neither in terms of economic magnitude nor statistical significance. The insignificant coefficients from the future number of bank closures support the parallel trends assumption. Taken together, these findings suggest that the expansion of crypto ATMs is partially a strategic response to declining access to traditional banking infrastructure. Firms appear to target regions experiencing reduced bank branch availability, positioning crypto ATMs as shadow intermediaries for unbanked individuals. Such finding is also consistent with our proposed mechanism: crypto ATMs serve as shadow intermediaries for unbanked and low-income households.

Second, we implement a difference-in-differences approach focusing on major county level bank closure and opening events within our sample. We define a county as ex-

[14]For more information about how crypto ATMs are designed, please see https://www.naag.org/attorney-general-journal/your-bitcoin-on-every-block-an-introduction-to-cryptocurrency-kiosks/ and https://optconnect.com/why-a-bitcoin-atm-needs-fast-reliable-secure-internet-connectivity/, in which the author documents that "Cryptocurrency kiosks (Crypto ATMs) are physical machines that allow customers to exchange cryptocurrencies for fiat currency or other cryptocurrencies. These machines are a combination cryptocurrency exchange and ATM. The physical manifestation of these devices is the unique characteristic, setting them apart from their online counterparts."

periencing a major event if it records more than 17 bank closures or more than 10 bank openings, the thresholds that place these county-year observations in the top 1% across all observations. Such events can lead to abrupt and large-scale shifts in banking accessibility within a county, which making it easy to identify the causal effects. The wide closure of bank branches is always driven by exogenous bank mergers, providing a clear setting for identifying causal effects. For the event study on major bank closures, regression estimates are presented in the Appendix Figure A14. In Appendix Table A24, we present the value of each estimated coefficient. The results indicate that large-scale bank branch closures have a significant and positive effect on crypto ATM installations. Counties affected by such events see approximately 10 additional crypto ATMs installed one year or more after the closure, compared to counties without such events. In contrast, major bank openings do not exhibit a similar effect. As shown in Appendix Table A25 and Appendix Figure A15, the opening of a large number of bank branches does not significantly influence the installation of crypto ATMs. These findings reinforce the notion that crypto ATM deployment is responsive to reductions in traditional banking access, rather than expansions.

Taken together, we assess our mechanism by documenting pronounced heterogeneous effects driven by variation in access to the traditional banking system: the installation of crypto ATMs has a significantly *greater* impact in regions with *limited* banking access. Combined with our findings in Table A13, this provides compelling evidence that crypto ATMs function as shadow intermediaries for unbanked individuals. Individuals may rely on them via their cryptocurrency accounts as an alternative channel to access fiat currency. Additionally, we find that crypto ATMs companies strategically allocate new installations in response to bank branch closures: regions experiencing more bank closures tend to see a greater number of crypto ATMs deployed. This pattern suggests that crypto ATMs are designed to serve as alternative intermediaries for unbanked individuals, with firms actively positioning themselves to capture market share in areas underserved by conventional financial institutions. Our conclusion provides valuable evidence on how people participate in the financial market (Vissing-Jorgensen, 2002; Campbell, 2006; Haliassos and Bertaut, 1995).

5.2 Welfare and Distribution

Our results allow for a first-pass assessment of the welfare trade-offs generated by the rapid expansion of crypto ATMs. On the benefit side, we document sizable increases in household financial participation, both in crypto assets themselves and, through spillovers, in stock-market engagement. We also find evidence of increased startup formation, suggesting that lower access frictions may stimulate real economic activity. These gains are consistent with long-standing models in household finance that emphasize how small reductions in participation costs can attract new investors to risky asset markets (Vissing-Jorgensen, 2002; Campbell, 2006).

We estimate that the overall annual welfare gain per county can be calculated as follows: cryptocurrency market participation gains ($125 \times 10 \times 150$), stock market participation gains ($60 \times 5 \times 50$), new adopters multiplied by the estimated consumer surplus from time saved (150×100), and small business loan formation translated into expected profits or employment ($3.4 \times 100{,}000$). Summing these components yields a total estimated annual pecuniary welfare gain per county of $557,500.

On the cost side, we find robust evidence of higher financial-fraud and identity-theft complaints following ATM expansion. These are not marginal nuisance outcomes: the categories we study (unauthorized transactions, identity theft, fraud complaints against banks and FinTech) represent substantial monetary losses for households, as well as enforcement costs for intermediaries and regulators. In addition, we document exploratory spillovers into illicit offline markets, including drug-overdose deaths and gun-related incidents. Although these latter effects are less precisely estimated, they point toward broader social externalities.

We estimate that the overall welfare loss per county, per year, can be calculated as follows: victim losses from identity theft or unauthorized transactions ($10 \times 20 \times 650$), and enforcement costs (15,000). Summing these components yields a total estimated annual welfare loss per county of $145,000. At the same time, the cost of overdose deaths represents a non-pecuniary loss that is hard to put a monetary value on.

As demonstrated by our simple welfare calculation, which employs conservative estimates of the monetary value of new participation as well as the losses associated with fraud and identity theft, we find that the net welfare effect is ambiguous—particularly when taking into account the various non-pecuniary costs and benefits. In some counties, particularly those with higher unbanked rates and fewer traditional financial outlets, the inclusion benefits appear to outweigh the fraud costs. In others, especially more affluent or already banked areas, the incremental participation gains are smaller while the fraud costs are more pronounced. This heterogeneity underscores that the welfare impact is not evenly distributed.

Distributional considerations are central. The participation gains we observe are concentrated among marginal, first-time adopters — often younger, less affluent, and more likely to be outside the traditional banking system. As illustrated in Appendix Table A26 and Appendix Table A27, regions characterized by greater internet access (higher rates of smartphone ownership), larger minority populations (Latino and Black communities), and lower income levels tend to exhibit greater receptivity to influence. These are precisely the groups that may benefit most from access to new payment rails and speculative assets, but they could also be more vulnerable to scams and identity theft. In contrast, the costs of increased fraud may fall disproportionately on victims nationwide, given the ease with which identity-theft complaints spread across jurisdictions. This mismatch between local benefits and diffuse costs creates a regulatory externality: local communities may welcome ATM expansion for the participation it brings, while the broader financial system bears the risks. Our supplementary empirical evidence reinforces this conclusion: Appendix Table A28 reveals a negative association between the installation of crypto ATMs and the regional Gini coefficient, suggesting that the emergence of the crypto market contributes to an increase in financial inclusion and a reduction in social inequality.

Taken together, the welfare evidence suggests that crypto ATMs trace out a privacy–inclusion–crime frontier. Moving along this frontier brings real financial engagement gains, but also increases exposure to fraud and illicit activity. Whether society is better off depends not only on the average treatment effect, but also on who gains, who loses, and how those costs and benefits are shared. These distributional patterns provide the foundation for the policy considerations we discuss next.

5.3 Crypto ATM Regulation

Our findings have direct implications for ongoing debates around the regulation of cryptocurrency ATMs and, more broadly, the design of financial-access policies. The evidence highlights a classic inclusion–oversight trade-off. On the one hand, crypto ATMs lower barriers to participation in digital finance, drawing in new households, expanding stock-market participation, and even supporting entrepreneurial activity. On the other hand, easier access to privacy-preserving payment rails also raises measurable fraud and identity-theft complaints, and produces suggestive spillovers into drug and firearm markets.

AML and KYC. Regulators have long used Know-Your-Customer (KYC) and Anti-Money Laundering (AML) rules to mitigate the risks of anonymity in financial transactions. Crypto ATMs present a challenge because they replicate the privacy of cash, but in digital form and with rapid scaling potential. Our evidence that ATM growth is associated with increased fraud complaints suggests that current compliance thresholds may be insufficient. One implication is the need for graduated verification regimes, such as requiring ID above modest transaction thresholds, or imposing stronger monitoring on operators with high-volume machines. This aligns with longstanding insights on financial regulation and access (Barth et al., 2008; Beck et al., 2007).

Consumer protection and financial literacy. A second implication concerns the profile of new adopters. Our event studies show sharp increases in engagement immediately after local exposure, consistent with ATMs drawing in, marginal, first-time users. Such households are more likely to be inexperienced and vulnerable to scams. Similarly to consumer credit markets (Gabaix and Laibson, 2006; Agarwal et al., 2015), policymakers may wish to require ATM operators to provide clear warnings, fraud-awareness prompts, or standardized fee disclosures. These "light-touch" measures could improve outcomes without undermining access.

Intermediary competition and liability. We also document that complaints shift toward banks and FinTechs after ATM adoption, suggesting that ATMs compete directly with incumbent payment rails. This raises questions about the allocation of responsibility for fraud losses. Should incumbent institutions bear the costs of disputes triggered by ATM-funded transactions, or should liability shift to ATM operators? Clarifying these boundaries would reduce uncertainty for both consumers and incumbents, echoing broader discussions of consumer protection concerning FinTech credit (e.g., Ru and Schoar, 2022).

In sum, our results indicate that crypto ATMs sit squarely on the privacy–inclusion–crime frontier that financial regulators have long navigated in the context of cash (Rogoff, 2017) and household financial participation (Vissing-Jorgensen, 2002; Campbell, 2006). Incremental reforms that tighten oversight without eliminating access may move this frontier outward. By quantifying both the participation gains and the fraud costs, our paper provides empirical input for designing such policies.

Taken together, these policy considerations underscore the central welfare question: how should regulators balance the participation gains we document against the external costs of fraud and illicit use? Our back-of-the-envelope welfare calculations provide one empirical benchmark, but the broader lesson is that policy design can shift the frontier. By calibrating AML/KYC thresholds and consumer protections, regulators may be able to preserve much of the inclusion benefit while sharply reducing the crime externalities.

6 Conclusion

We present empirical evidence on both the positive and negative effects of general cryptocurrency adoption on the main street enabled by crypto ATMs. On the one hand, crypto ATMs enhance financial inclusion and engagement, not only within the cryptocurrency ecosystem but also across traditional financial markets, including the stock market. On the other hand, their presence is associated with an increase in financial-related criminal activity. The unregulated nature of cryptocurrency trading appears to facilitate an increase in illegal financial behavior, which intensifies as the number of crypto ATMs grows. Moreover, our findings suggest that crypto ATMs stimulate regional entrepreneurial activity, contributing to the growth of startups and small businesses. However, their presence is also positively correlated with an increase in overdose-related fatalities and incidents involving gun violence.

Our findings demonstrate that lowering access frictions to cryptocurrency through physical ATMs produces significant changes in household financial behavior and local economic activity. The findings highlight a central tension created by decentralized financial infrastructure: increased participation and convenience arrive with reduced oversight and greater exposure to misconduct. Understanding how to design regulatory frameworks that preserve the inclusion benefits while mitigating the associated risks is therefore an important direction for future work. More broadly, our evidence underscores the need to evaluate emerging financial technologies not only through their digital architecture but also through the channels by which they interact with households, intermediaries, and the real economy.

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Figures and Tables

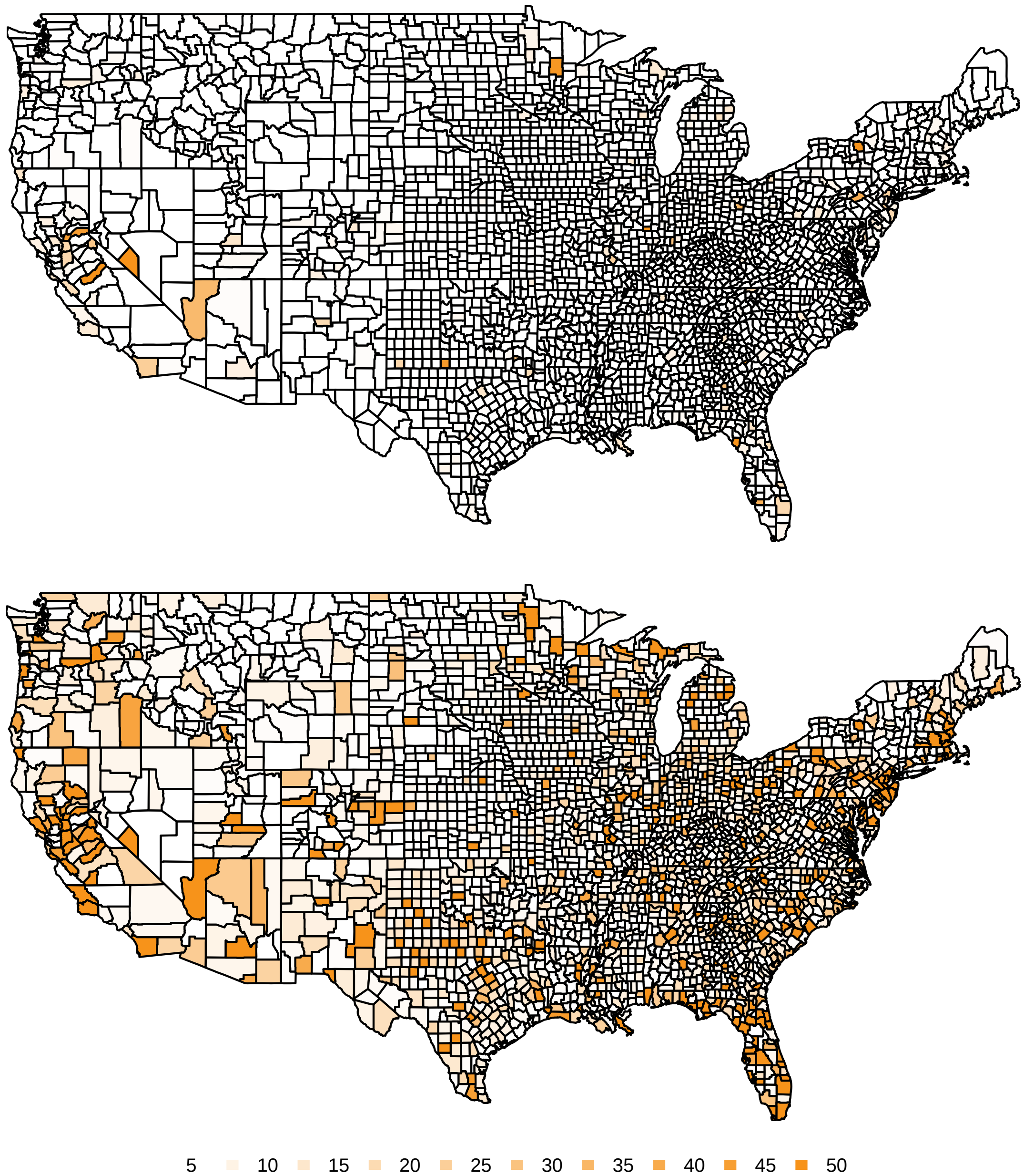


Figure 1: Growth of Crypto ATMs by County, 2018–2022

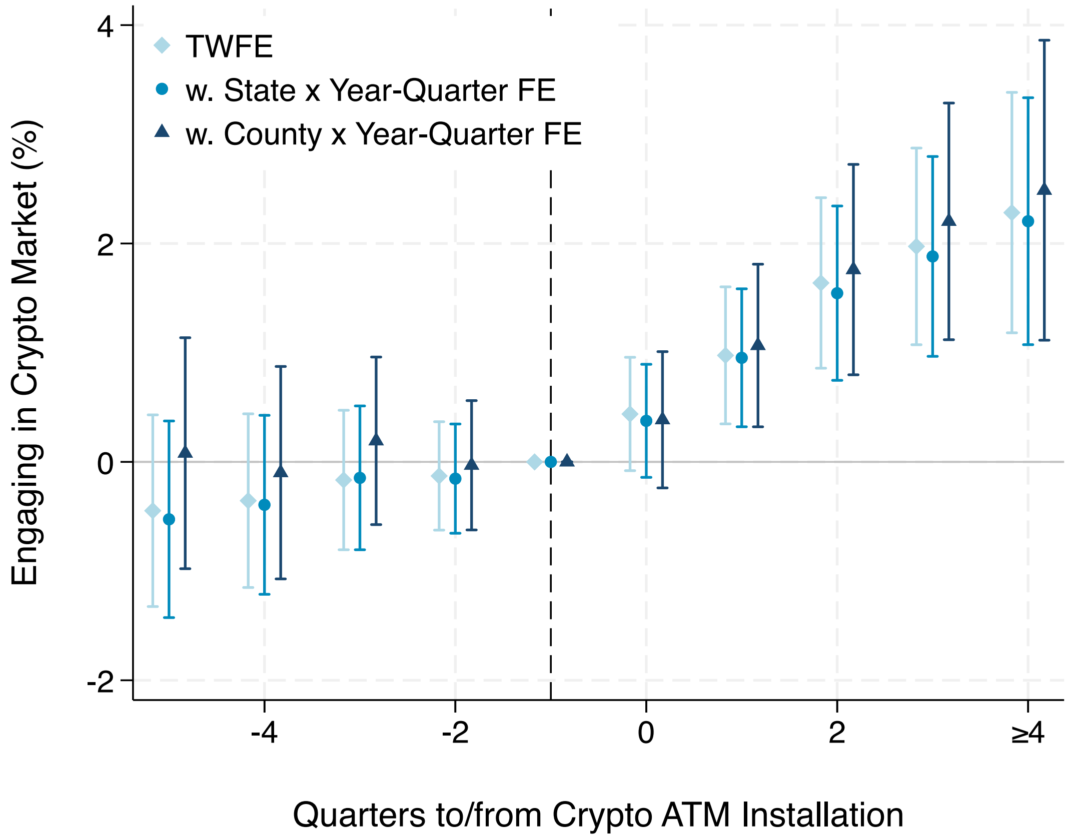


Figure 2: The Dynamic Impact of Crypto ATMs Installation on Individuals' Engagement in Crypto Market

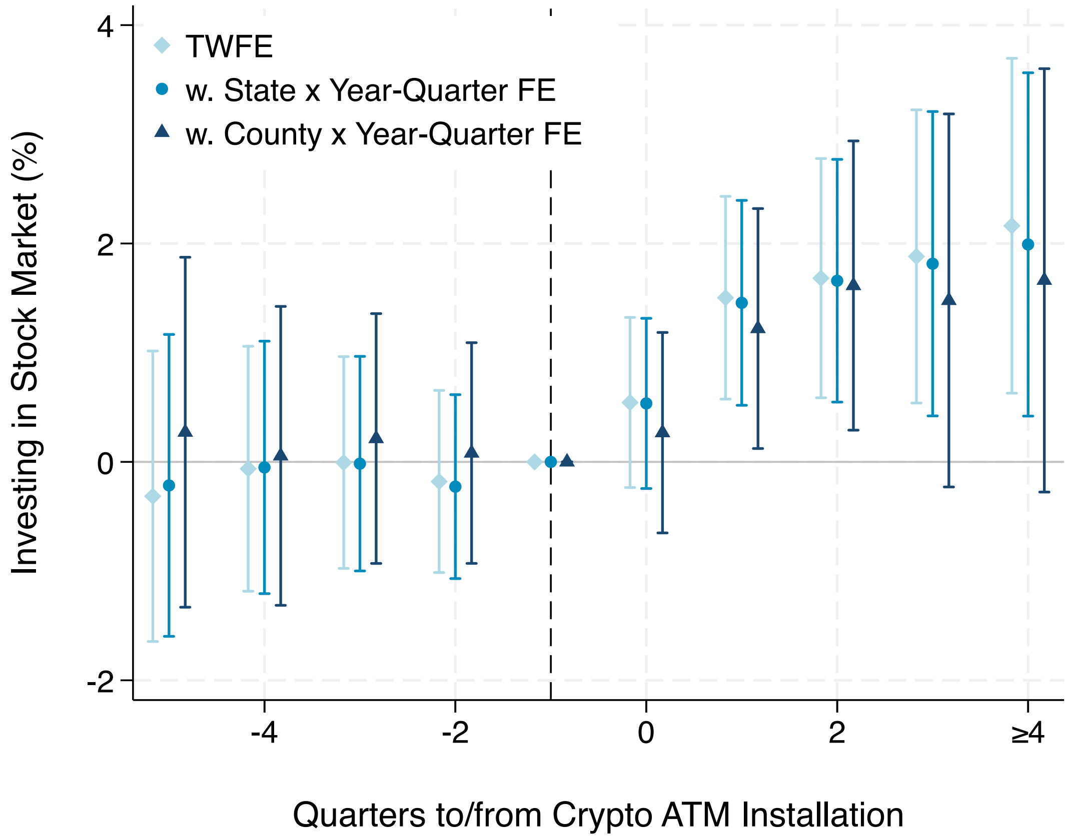


Figure 3: The Dynamic Impact of Crypto ATMs Installation on Individuals' Engagement in Stock Market

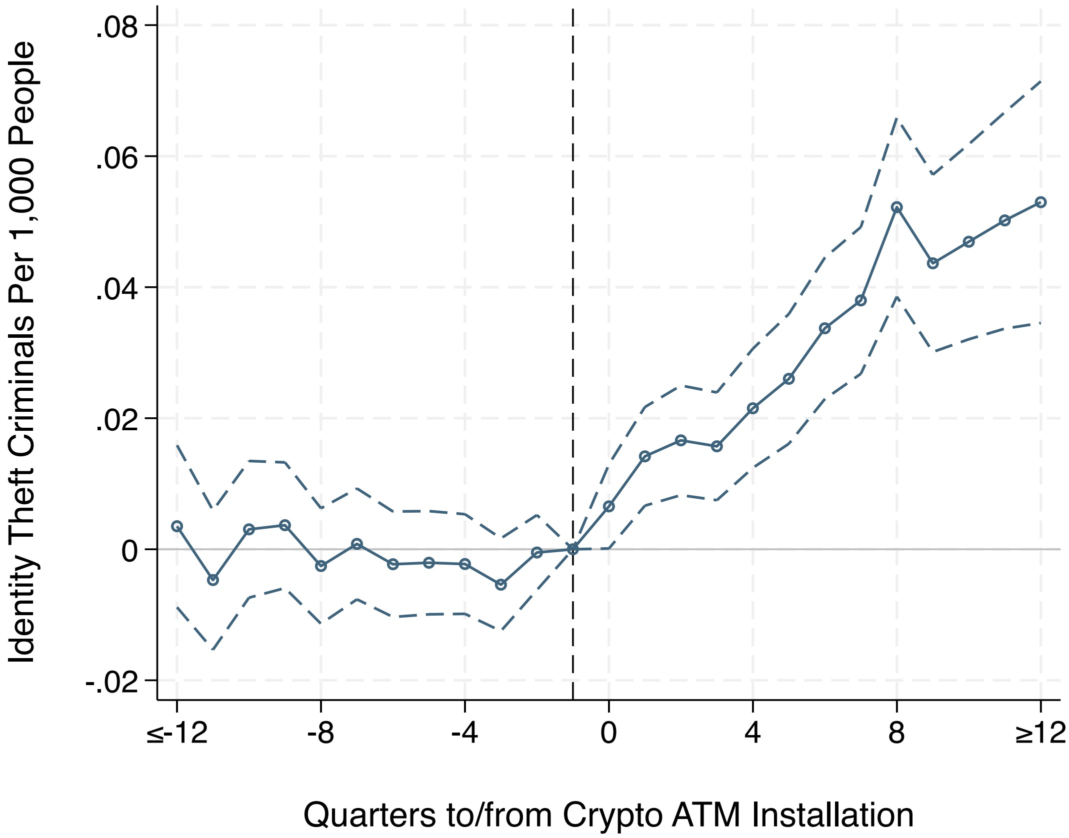


Figure 4: The Dynamic Impact of Crypto ATMs Installation on Regional Criminal Reports for Identity Theft Behaviors

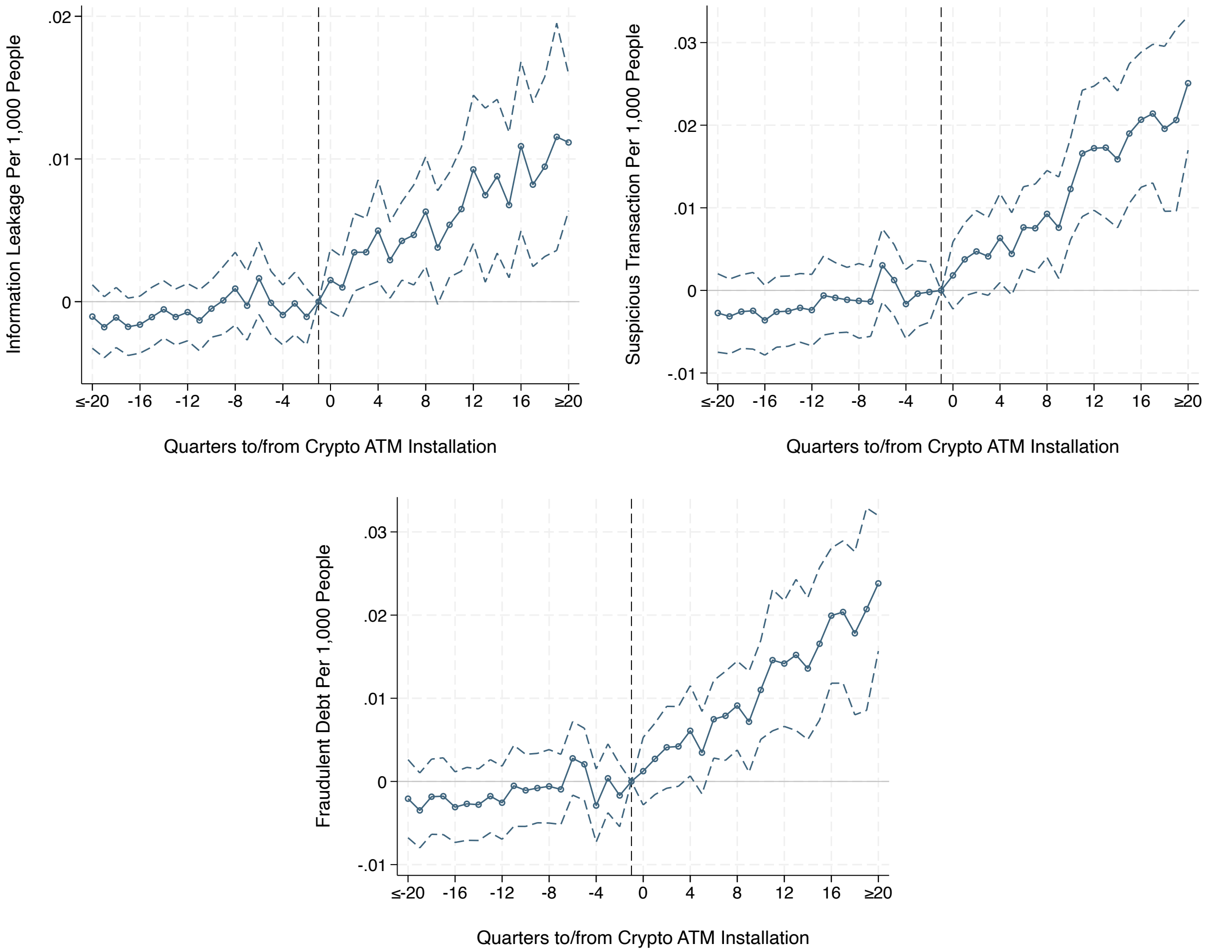


Figure 5: The Dynamic Impact of Crypto ATMs Installation on Regional Financial Fraud Reports

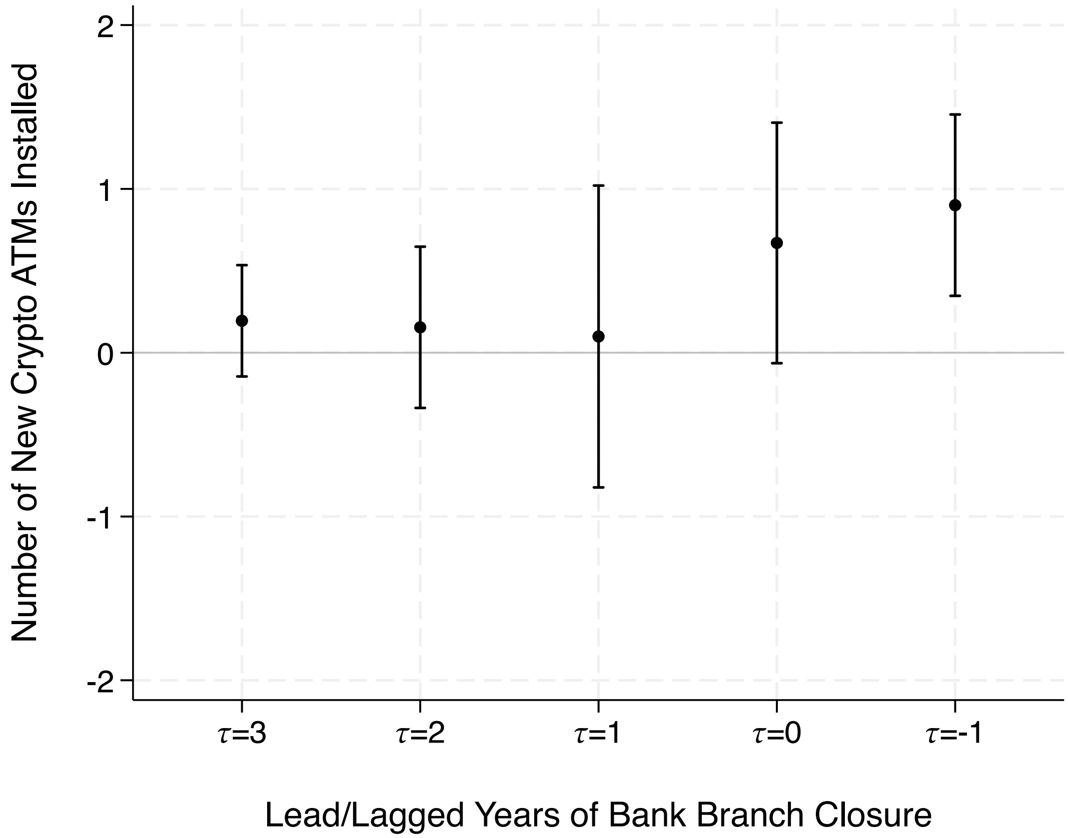


Figure 6: The Pre-Trend Test on Banks Closure and Crypto ATMs' Installation

Table 1: Summary Statistics

	Mean	S.D.	Obs.
	(1)	(2)	(3)
Panel A: Crypto ATMs			
Number of Crypto ATMs	3.24	20.75	84,512
Panel B: Consumer App Usage			
Using Crypto Apps ($\times$ 100)	7.77	26.78	1,190,431
Using Stock Apps ($\times$ 100)	14.05	34.76	1,190,431
Panel C: Crimes			
Cybercriminal Rate			
... of Identity Theft	0.0719	0.1467	47,456
... of Other Cybercrimes	0.6913	0.6385	47,456
Panel D: Financial Fraud Reports			
Financial Fraud Rate			
... of Information Leakage	0.0062	0.0502	84,512
... of Suspicious Transaction	0.0200	0.0785	84,512
... of Fraudulent Debt	0.0211	0.0799	84,512

Note: This table presents our summary statistics, including the mean value, standard deviation, and total number of observations of each variable. Panel A presents a county-level summary of the number of crypto ATMs at quarterly frequency, spanning from the first quarter of 2013 to the last quarter of 2022, a total of 40 year-quarters. For further details on the expansion of crypto ATMs, please refer to Figure 1 and the Appendix Table A1. Panel B presents individual-level summary statistics for users who engage with cryptocurrency-related and stock-related apps. Engagement is captured using a dummy variable, which is set to one if the user interacts with crypto or stock-related apps during a given quarter, and zero otherwise. This variable is based on data from 466,851 individuals between 2019 and 2022, covering 16 year-quarters. Panel C reports criminal rates at the police agency level, calculated as the total number of criminal incidents divided by the population, multiplied by 1,000, that is, crimes per 1,000 capita. The dataset includes 1,598 police agencies and spans from 2015 to 2022, totaling 32 year-quarters. Panel D summarizes county-level consumer complaints related to financial fraud, measured as the number of fraud reports per 1,000 capita, that is, total financial fraud reports divided by population, then multiplied by 1,000. This panel covers the period from 2013 to 2022, also totaling 40 year-quarters. For more details on the categories of consumer complaints, please refer to Appendix Table A2.

Table 2: Crypto ATMs and Crypto Market Engagement: Shift-Share Instrumental Variable Approach

	Using Crypto Apps (×100)				
	(1)	(2)	(3)	(4)	(5)
Instrumented Num. of Crypto ATMs	0.1432***	0.1211**	0.1571***	0.1643***	0.1122*
	(0.0533)	(0.0558)	(0.0573)	(0.0576)	(0.0663)
R^2	0.038	0.038	0.038	0.081	0.647
Mean of D.V.	7.78	7.78	7.78	7.78	7.78
Num. of Indviduals	467,829	467,817	467,817	466,842	244,236
Num. of Zipcodes	20,423	20,421	20,421	18,882	18,907
Num. of Counties (Clusters)	2,724	2,724	2,724	2,713	2,711
N	1,190,374	1,190,359	1,190,359	1,188,820	966,796
County FE	Yes	Yes	Yes		Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Control		Yes	Yes	Yes	Yes
State FE × Bitcoin Price			Yes	Yes	Yes
Zip Code FE				Yes	
Individual FE					Yes

Note: This table presents the impact of crypto ATM installation on individuals' decisions to engage in the crypto market. We use Bartik-style instrumental variable with two-stage least square (2SLS) approach to estimate the coefficients. To be specific, we report the second-stage regression coefficients of the IV approach. The baseline regression model is: $EngageCrypto_{czit} = \beta \widehat{NumCryptoATMs}_{ct} + Year\text{-}Quarter\ FE + County\ FE + Control + \varepsilon_{czit}$, in which $EngageCrypto_{czit}$ equals one if individual i in zipcode z of county c uses crypto-related apps within year-quarter t and zero otherwise. $\widehat{NumCryptoATMs}_{ct}$ is the Shift-Share instrumental variable predicted number of crypto ATMs for county c of year-quarter t. We report the first-stage regression at Appendix Table A5. The baseline model includes a full set of county and time fixed effects, as well as macroeconomic control variables, including population, income, and total number of employment. We additionally provide the estimated coefficients with other fixed effects, such as state fixed effects times bitcoin price, zip code fixed effects, or individual fixed effects. We cluster our standard-errors at the county level. Every coefficient and standard error are multiplied by 100. Significance: * 10%; ** 5%; *** 1%.

Table 3: Crypto ATMs and Crypto Market Engagement: Individual-Level Quasi-Natural Experimental Evidence

	Using Crypto Apps (×100)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Baseline (Excluding Always-Treated Group)					
Post Crypto ATM Installation	0.7124**	0.7083**	0.7984***	0.7445***	0.6763**
	(0.3446)	(0.3444)	(0.2693)	(0.2695)	(0.3272)
R^2	0.261	0.261	0.516	0.522	0.592
Mean of D.V.	7.58	7.58	7.58	7.58	7.58
Num. of Indviduals	9,441	9,441	9,440	9,440	9,217
Num. of Zipcodes	5,750	5,743	6,582	6,582	6,081
Num. of Counties (Clusters)	1,348	1,348	1,431	1,431	1,005
N	102,213	102,179	103,017	103,015	97,076
Panel B: Additional Identification: Including Early-Treated Individuals in Control Group					
Post Crypto ATM Installation	−0.3329	−0.3380	0.5750**	0.6772**	0.7509**
	(0.3666)	(0.3668)	(0.2705)	(0.2668)	(0.3116)
R^2	0.233	0.233	0.529	0.533	0.589
Mean of D.V.	8.09	8.09	8.09	8.09	8.09
Num. of Indviduals	12,258	12,258	12,257	12,257	12,033
Num. of Zipcodes	6,390	6,383	7,143	7,143	6,668
Num. of Counties (Clusters)	1,407	1,407	1,486	1,486	1,068
N	131,137	131,101	131,860	131,858	126,004
Zip Code FE	Yes	Yes			
Year-Quarter FE	Yes	Yes	Yes		
Control		Yes	Yes	Yes	Yes
Individual FE			Yes	Yes	Yes
State × Year-Quarter FE				Yes	
County × Year-Quarter FE					Yes

Note: This table presents the impact of crypto ATM installation on individuals' decisions to engage in the crypto market. We employ the installation of crypto ATMs as a quasi-natural experiment to examine how their presence influences individuals' decisions to participant in the cryptocurrency market. The baseline regression model is: $EngageCrypto_{czit} = \beta PostCryptoATM_{it} + County \times Year\text{-}Quarter\ FE + Individual\ FE + Control + \varepsilon_{czit}$, in which *EngageCrypto* equals one if a given individual uses crypto-related apps within a given year-quarter and zero otherwise. The event-study extension is in Figure 2. The sample period is from 2019 to 2022, totaling 16 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table 4: Crypto ATMs and Stock Market Engagement

	Using Stock Apps (×100)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Shift-Share IV Estimation					
Instrumented Num. of Crypto ATMs	0.1308**	0.0805	0.0918	0.0930	−0.0197
	(0.0660)	(0.0678)	(0.0701)	(0.0711)	(0.0905)
R^2	0.019	0.019	0.019	0.069	0.665
Mean of D.V.	14.05	14.05	14.05	14.05	14.05
N	1,190,355	1,190,340	1,190,340	1,188,802	966,776
County FE	Yes	Yes	Yes		Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Control		Yes	Yes	Yes	Yes
State FE × Bitcoin Price			Yes	Yes	Yes
Zip Code FE				Yes	
Individual FE					Yes
Panel B: Difference-in-Differences Approach					
Post Crypto ATM Installation	1.4443***	1.4487***	0.9580**	0.9719**	0.6097
	(0.4660)	(0.4647)	(0.3730)	(0.3786)	(0.4417)
R^2	0.276	0.276	0.593	0.596	0.652
Mean of D.V.	18.37	18.37	18.37	18.37	18.37
N	102,213	102,179	103,017	103,015	97,076
Zip Code FE	Yes	Yes			
Year-Quarter FE	Yes	Yes	Yes		
Control		Yes	Yes	Yes	Yes
Individual FE			Yes	Yes	Yes
State × Year-Quarter FE				Yes	
County × Year-Quarter FE					Yes

Note: This table shows the impact of crypto ATM installation on individuals' decision to engage in the stock market. The sample period is from 2019 to 2022, totaling 16 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table 5: Crypto ATM Adoption and Entrepreneurial Activity

	(1)	(2)
A.1 Number of Small Business Loan Applications Per 1,000 Capita		
Instrumented Num. of Crypto ATMs	0.000448	0.003478***
	(0.0004)	(0.0012)
R^2	0.520	0.554
A.2 Amount of Business Loans (in U.S. Dollar) Per 1,000 Capita		
Instrumented Num. of Crypto ATMs	432.2169**	1526.8927**
	(220.0823)	(596.1569)
R^2	0.287	0.287
Sample	Full	Pre-COVID
Control	Yes	Yes
County FE	Yes	Yes
Year-Quarter FE	Yes	Yes
N	84,510	59,154

Note: This table presents the downstream impact of the increased financial participation rate from crypto ATMs' installation. To be specific, we present how crypto ATM installation influences regional startup formations. The baseline regression model is $Outcome_{ct} = \beta Num\widehat{CryptoATM}_{ct} + Control + County\ FE + Year\text{-}Quarter\ FE + \varepsilon_{ct}$, in which $Num\widehat{CryptoATM}$ is the Shift-Share instrumented number of crypto ATMs. The first stage regression is reported in Appendix Table A5. The sample period is from 2013 to 2022, totaling 40 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table 6: Crypto ATMs and Cybercriminal Behaviors

	Identity Theft Criminals Per 1,000 Capita			
	(1)	(2)	(3)	(4)
Panel A: Identity Theft Criminals				
Post Crypto ATM Installation	0.0192***	0.0197***	0.0148***	0.0140***
	(0.0035)	(0.0033)	(0.0032)	(0.0032)
R^2	0.492	0.546	0.615	0.688
Mean of D.V.	0.07	0.07	0.07	0.07
Panel B: Other Cybercrimes				
Post Crypto ATM Installation	−0.0151	−0.0110	−0.0079	−0.0072
	(0.0097)	(0.0094)	(0.0094)	(0.0096)
R^2	0.669	0.675	0.719	0.765
Mean of D.V.	0.69	0.69	0.69	0.69
Control	Yes	Yes	Yes	Yes
Police Agency FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes		
State FE × Bitcoin Price		Yes		
State × Year-Quarter FE			Yes	Yes
Police Agency-Level Linear Trend				Yes
N	47,456	47,456	47,417	47,417

Note: This table presents our Difference-in-Differences estimation of the impact of crypto ATM installation on regional online criminal reports. The baseline regression model is: $CyberCrimeRate_{pt} = \beta PostCryptoATM_{pt} + Control + Police\ Agency\ FE + Year\text{-}Quarter\ FE + \varepsilon_{pt}$. *CyberCrimeRate* is calculated as the total number of cyber-criminals per 1,000 capita. $PostCryptoATM_{pt}$ equals one on or after the first crypto ATM installed at the region for a given police-agency. In Panel A, the dependent variable is the total number of identity theft criminals per 1,000 capita for each quarter. In Panel B, the dependent variable is the incidence of all other types of cybercrime. The event study extension of Panel A results is reported in Figure 4. The sample period is from 2015 to 2022, totaling 32 year-quarters. We cluster our standard-errors at police agency level. Significance: * 10%; ** 5%; *** 1%.

Table 7: Crypto ATMs and Financial Frauds Consumer Reports: Different Categories

	Reported Financial Fraud Per 1,000 Capita		
	(1) Information Leakage	(2) Suspicious Transaction	(3) Fraudulent Debt
Panel A: County-Level Instrumental Variable Estimation			
Instrumented Num. of Crypto ATMs	0.000291***	0.000749***	0.000524**
	(0.0001)	(0.0002)	(0.0002)
R^2	0.201	0.301	0.305
Control	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Mean of D.V.	0.0062	0.0200	0.0211
N	84,512	84,512	84,512
Panel B: Zip Code-Level Difference-in-Differences Estimation			
Post Crypto ATM Installation	0.002930***	0.004170***	0.004003***
	(0.0010)	(0.0013)	(0.0013)
R^2	0.251	0.307	0.304
Control	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes
County × Year-Quarter FE	Yes	Yes	Yes
Mean of D.V.	0.0126	0.0383	0.0396
N	279,724	279, 724	279,724

Note: This table presents the estimation of the impact of crypto ATM installation on regional financial fraud reports. Panel A uses 2SLS regression with Shift-Share instrumental variable on county-level regional financial fraud reports. The baseline regression model is $FinFraudRate_{ct} = \beta Num\widehat{CryptoATMs}_{ct} + Control + County\ FE + Year\text{-}Quarter\ FE + \varepsilon_{ct}$, in which $Num\widehat{CryptoATMs}$ is the Shift-Share instrumented number of crypto ATMs. *FinFraudRate* is calculated as the total number of financial fraud reports per 1,000 capita. The first stage regression is reported in Appendix Table A5. We include a full set of county-level and time fixed effects in our regression, as well as macroeconomic control variables including population, income, and total number of employments. Panel B presents difference-in-differences identification strategy on zip code-level regional financial fraud reports. The baseline regression model is $FinFraudRate_{czt} = \beta PostCryptoATM_{czt} + Control + Zip\ Code\ FE + County \times\ Year\text{-}Quarter\ FE + \varepsilon_{czt}$. *PostCryptoATM* equals one if the first crypto ATMs is installed on or before a given year-quarter for a zip code. We include zip code fixed effects, county and time joint fixed effects, as well as some zip code-level macroeconomic factors including population and income in our regression. The event study extension of the DiD estimation of Panel B is in Figure 5. The sample period is from 2013 to 2022, totaling 40 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table 8: Crypto ATM Installation and Financial Fraud Consumer Reports: Different Firms

	Financial Fraud Reports Per 1,000 Capita				
	Traditional Financial Firms			Online/Digital Financial Firms	Credit Service Firms
	(1) Bank & Traditional Financial Service	(2) Investment & Asset Management	(3) Credit Card & Loan	(4) Financial Technology	(5) Credit Scoring
Panel A: County-Level Instrument Variable Estimation					
Instrumented Num. of Crypto ATMs	0.000474***	0.000043***	0.000283**	0.000112***	0.000439*
	(0.0001)	(0.0000)	(0.0001)	(0.0000)	(0.0002)
R^2	0.219	0.128	0.262	0.165	0.268
Control	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Mean of D.V.	0.0086	0.0007	0.0128	0.0008	0.0087
N	84,510	84,510	84,510	84,510	84,510
Panel B: Zip Code-Level Difference-in-Difference Estimation					
Post Crypto ATM Installation	0.001796***	0.000073	0.001638***	0.000216*	0.001602**
	(0.0004)	(0.0001)	(0.0005)	(0.0001)	(0.0008)
R^2	0.250	0.148	0.267	0.166	0.358
Control	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes	Yes	Yes
County × Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Mean of D.V.	0.0178	0.0017	0.0249	0.0020	0.0185
N	279,724	279,724	279,724	279,724	279,724

Continued

Total Financial Fraud Reports	37,981	4,761	66,278	2,586	28,443
... of Information Leakage	10,921(28.75%)	611(12.83%)	9,220(13.91%)	186(7.19%)	2,837(9.97%)
... of Suspicious Transaction	17,135(45.11%)	3,544(74.44%)	52,505(79.22%)	1,044(40.37%)	5,912(20.79%)
... of Fraudulent Debt	11,785(31.03%)	4,466(93.80%)	64,092(96.70%)	989(38.24%)	6,246(21.96%)
... of Reporting Issues About Fraud	-	-	-	-	21,971(77.25%)

Note: This table replicates the main specification in Table 7, but categorizes the financial fraud reports by type of financial institution involved in the consumer complaints. The sample period is from 2013 to 2022, totaling 40 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table 9: The Illicit Spillover of Crypto ATMs' Installation: Drug and Gunshots

	(1)	(2)	(3)	(4)
Panel A: Drug Consumption				
Overdose-Caused Deaths Per 1,000 Capita				
Instrumented Num. of Crypto ATMs	0.001514***	0.000806***	0.001279***	0.000653***
	(0.0002)	(0.0001)	(0.0002)	(0.0002)
R^2	0.726	0.708	0.734	0.713
Alcohol-Caused Deaths Per 1,000 Capita (Placebo)				
Instrumented Num. of Crypto ATMs	0.000196	0.000196	−0.000089	−0.000089
	(0.0148)	(0.0227)	(0.0183)	(0.0268)
R^2	0.756	0.744	0.778	0.780
Sample	Full	Large	Pre-COVID	Large & Pre-COVID
Control	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
N	47,222	14,110	41,318	12,346
Panel B: Block-Level Gunshots Reports in Minneapolis				
Post Crypto ATM Installation	0.8095**	0.7037*	0.1687**	0.6095**
	(0.3348)	(0.4256)	(0.0739)	(0.2564)
R^2	0.788	0.768	0.594	0.766
Sample	All	Frequent Shoots	Day Time	Overnight
Block FE	Yes	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes	Yes
N	20,352	9,936	20,352	20,352

Note: This table presents the illicit-use spillovers of crypto ATM's installation. In Panel A, we present the instrumental variable estimation of the impact of crypto ATM installation on regional over-dose caused deaths. The baseline regression model is $Outcome_{ct} = \beta Num\widehat{Crypto}ATM_{ct} + Control + County\ FE + Year\text{-}Quarter\ FE + \varepsilon_{ct}$, in which $Num\widehat{Crypto}ATMs$ is the Shift-Share instrumented number of crypto ATMs. In Panel B, we present a event study of crypto ATM installation on regional gunshot reports. We run the following regression: $NumGunShot_{b,t} = \beta PostCryptoATM_{b,t} + Block\ FE + Year\text{-}Quarter\ FE + \varepsilon_{b,t}$. We report the estimated coefficients based on gunshot reports across four categories: all blocks in Minneapolis, blocks with the highest frequency of gunshots, daytime gunshots reports, and overnight occurrences. The event-study extension of Panel B is documented at Appendix Figure A12. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table 10: Assessing Mechanism: Heterogeneity by Accessibility to Banking System

Panel A: Crypto Market Engagement

	Using the Apps (×100)		
	(1) All Crypto Apps	(2) *Crypto.com*	(3) Central Crypto Exchange
Instrumented Num. of Crypto ATMs	−0.0627*	−0.0383**	−0.0581*
× Banks Per Capita (Standardized)	(0.0340)	(0.0182)	(0.0321)
Instrumented Num. of Crypto ATMs	−0.0890	−0.0844***	−0.0656
× High Bank Accessibility Dummy	(0.0549)	(0.0270)	(0.0516)

Panel B: Financial Fraud

	Reported Financial Fraud Per 1,000 Capita		
	(1) Information Leakage	(2) Suspicious Transaction	(3) Fraudulent Debt
Instrumented Num. of Crypto ATMs	−0.000193***	−0.000477***	−0.000441***
× Banks Per Capita (Standardized)	(0.0000)	(0.0001)	(0.0001)
Instrumented Num. of Crypto ATMs	−0.000420***	−0.001126***	−0.001050***
× High Bank Accessibility Dummy	(0.0001)	(0.0002)	(0.0002)
Instrumented Num. of Crypto ATMs	Yes	Yes	Yes
Control	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes

Note: This table presents heterogeneous impact of crypto ATM installation by regional accessibility to commercial banks. We estimate 2SLS regression with Shift-Share instrumental variable on county-level regional financial fraud reports. The baseline regression model is $Outcome_{c(zi)t} = \beta_1 Num\widehat{CryptoATMs}_{ct} \times BankAccess_c + \beta_2 Num\widehat{CryptoATMs}_{ct} + Control + County\ FE + Year\text{-}Quarter\ FE + \varepsilon_{ct}$. We estimate the bank accessibility before our sample starts. We include a full set of county-level and time fixed effects in our regression, as well as macroeconomic control variables including population, income, and total number of employments. In the Appendix Table A20, we present the OLS estimation of each coefficient. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table 11: Assessing Mechanism: Predicting the Number of New Crypto ATMs Installation with the Number of Banks

	Number of New Crypto ATMs Installed			
	(1)	(2)	(3)	(4)
Total Number of Banks (Lagged 1 Year)	−0.5406***	−0.6009***		
	(0.1322)	(0.1368)		
Number of Banks Closed (Lagged 1 Year)			0.9662***	0.9007***
			(0.2975)	(0.2824)
Number of Banks Opened (Lagged 1 Year)			−0.4548	−0.4557
			(0.7401)	(0.7179)
R^2	0.753	0.778	0.745	0.766
Control	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes
Year FE	Yes		Yes	
State × Year FE		Yes		Yes
N	15,188	15,185	15,188	15,185

Note: In this table, we predict the number of new crypto ATMs installed by the one-year lagged number of banks. We resample our data to annual-frequency, as the number of banks is an annual data. We run the following regression: $NumNewCryptoATM_{ct} = \beta_1 NumBankClose_{ct-1} + \beta_2 NumBankOpen_{ct-1} + Control + State \times Year\ FE + County\ FE + \varepsilon_{ct}$, in which $NumBankClose_{ct-1}$ is one year lagged number of bank branches closed in county c of year $t-1$, and $NumBankOpen_{ct-1}$ is one year lagged number of new banks open of county c in year $t-1$. We include state-year joint fixed effects to avoid the influence by state-level crypto and bank-related regulations. A full set of macroeconomic control, including population, income, and employment are included. We cluster our standard-errors at the county level. We provide additional identification on such relationship in Figure 6 and Appendix Table A23, in which we conduct pre-trend analysis by "predicting" new crypto ATMs installation with future bank closure and opening. Significance: * 10%; ** 5%; *** 1%.

Appendix

Figure A1: An Example of Crypto ATMs

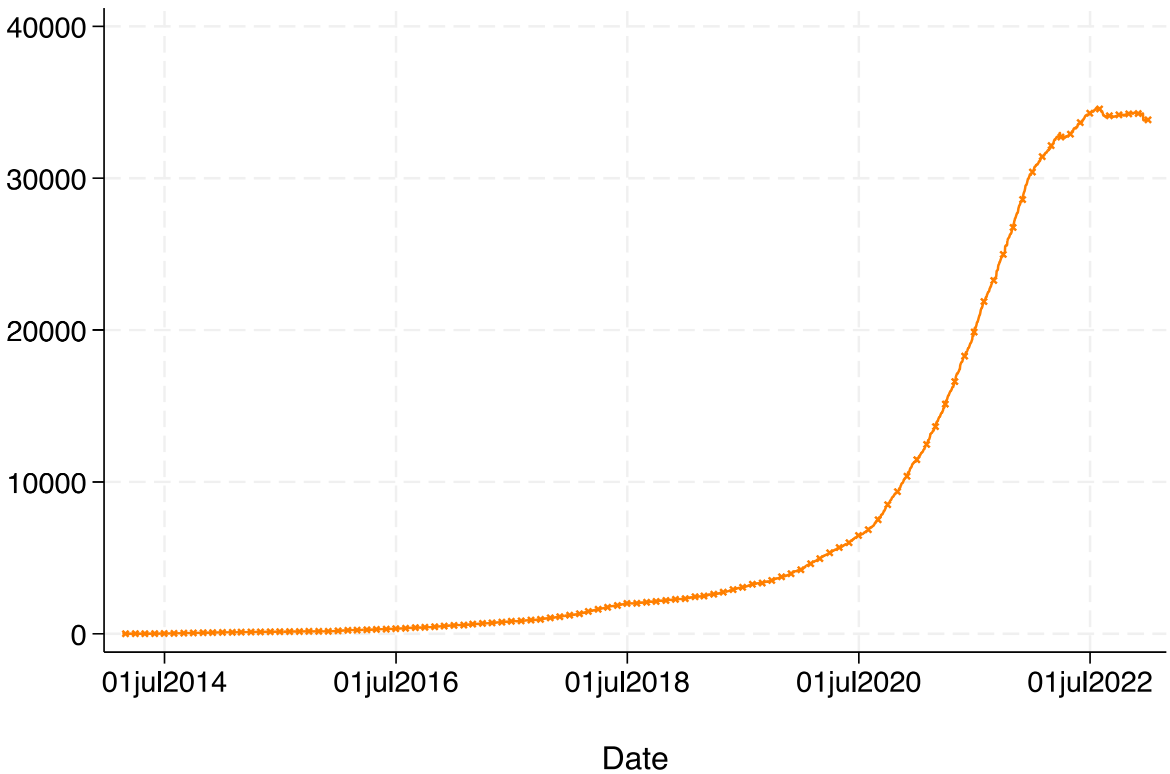


Figure A2: Number of Crypto ATMs in the United States Over Time

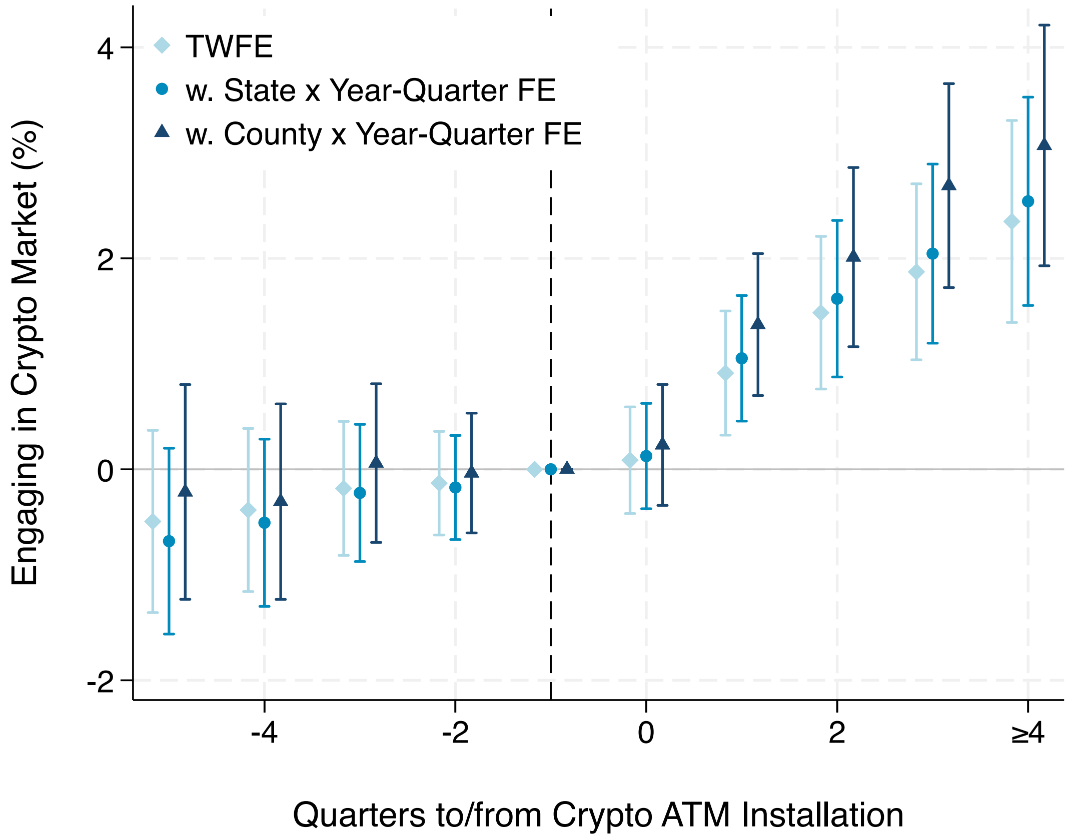
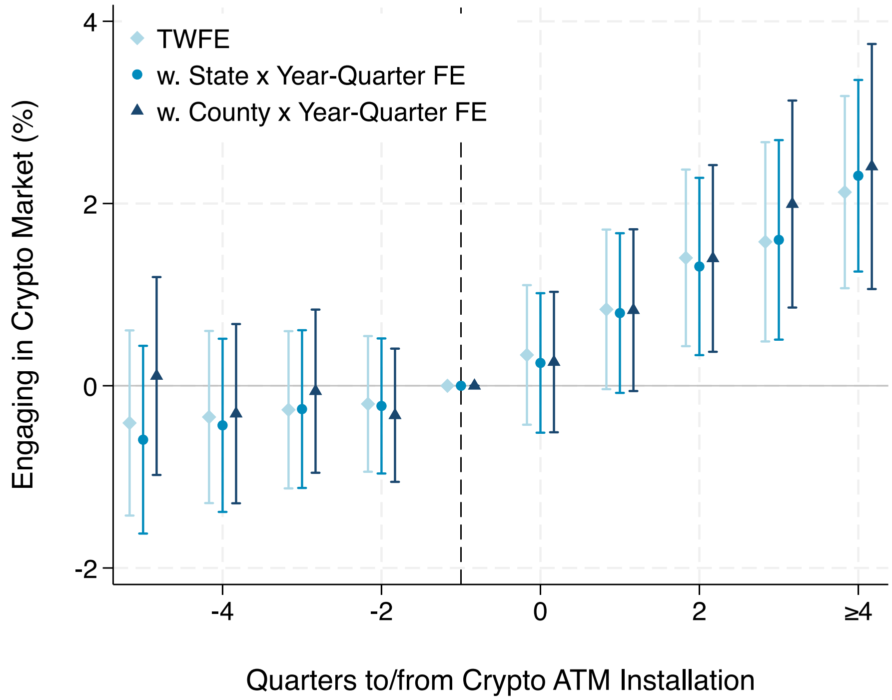


Figure A3: The Dynamic Impact of Crypto ATMs Installation on Individuals' Engagement in Crypto Market: With Early Treated As Control

Panel A: Excluding Always-Treated Group



Panel B: Including Early-Treated Individuals in Control Group

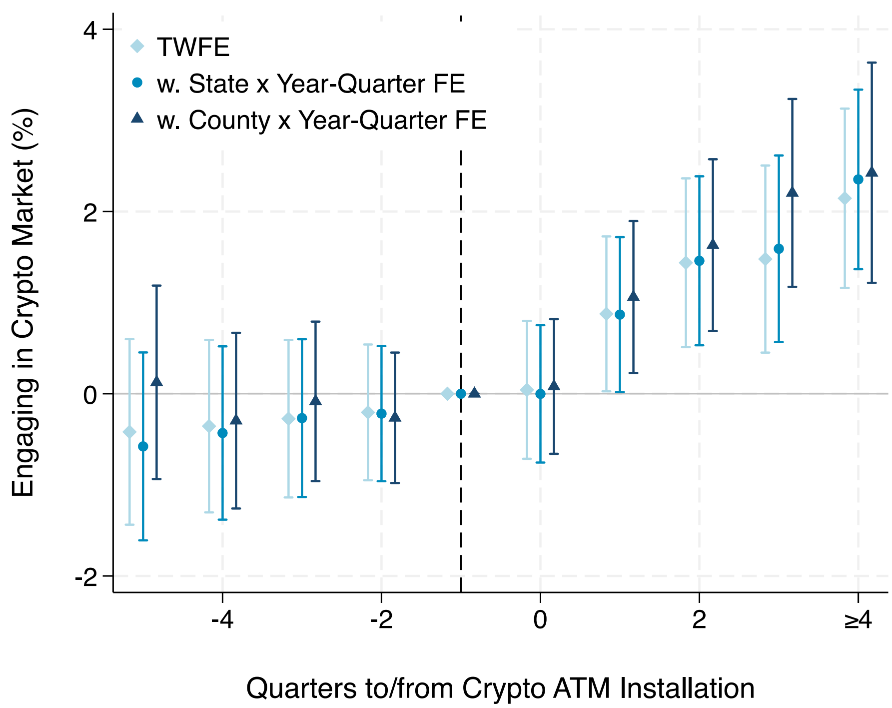


Figure A4: The Dynamic Impact of Crypto ATMs Installation on Individuals' Engagement in Crypto Market, Using Stacked Difference-in-Differences Strategy crypto.com | RESEARCH Crypto.com | 6

1. Headline Findings and Key Trends

1.1 Headline Findings

The Crypto.com Visa Card saw more than 80% growth in total spending in 2022 compared to the previous year. Particularly, we noticed considerable growth in the following categories:

Recreation	Transportation	Hotels & Dining	In-store	Online
52%	29%	28%	-12%	5%

Figures in this section show each category's growth relative to overall spending growth in 2022 versus 2021.

1.2 Key Trends

Grocery remains the main spending category, accounting for 36% of volume in 2022.

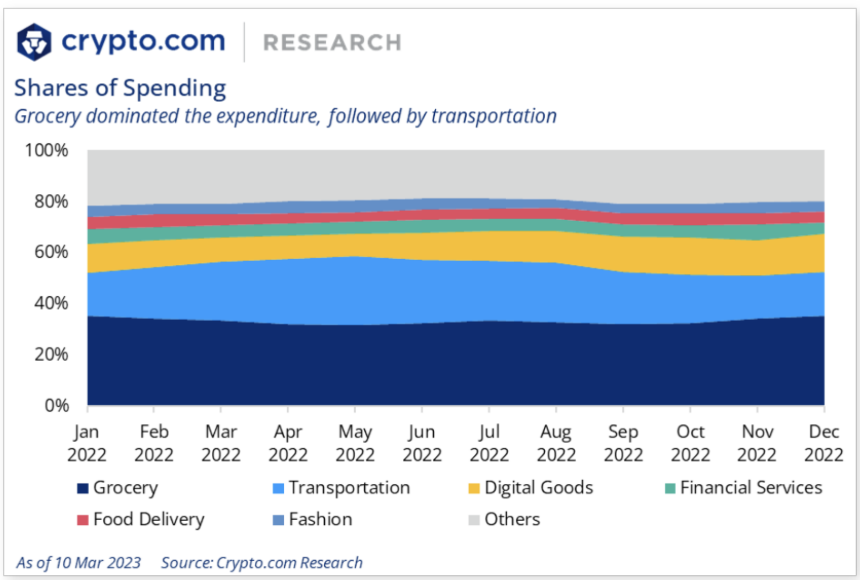


Figure A5: *Crypto.com* Consumer Reports of 2022

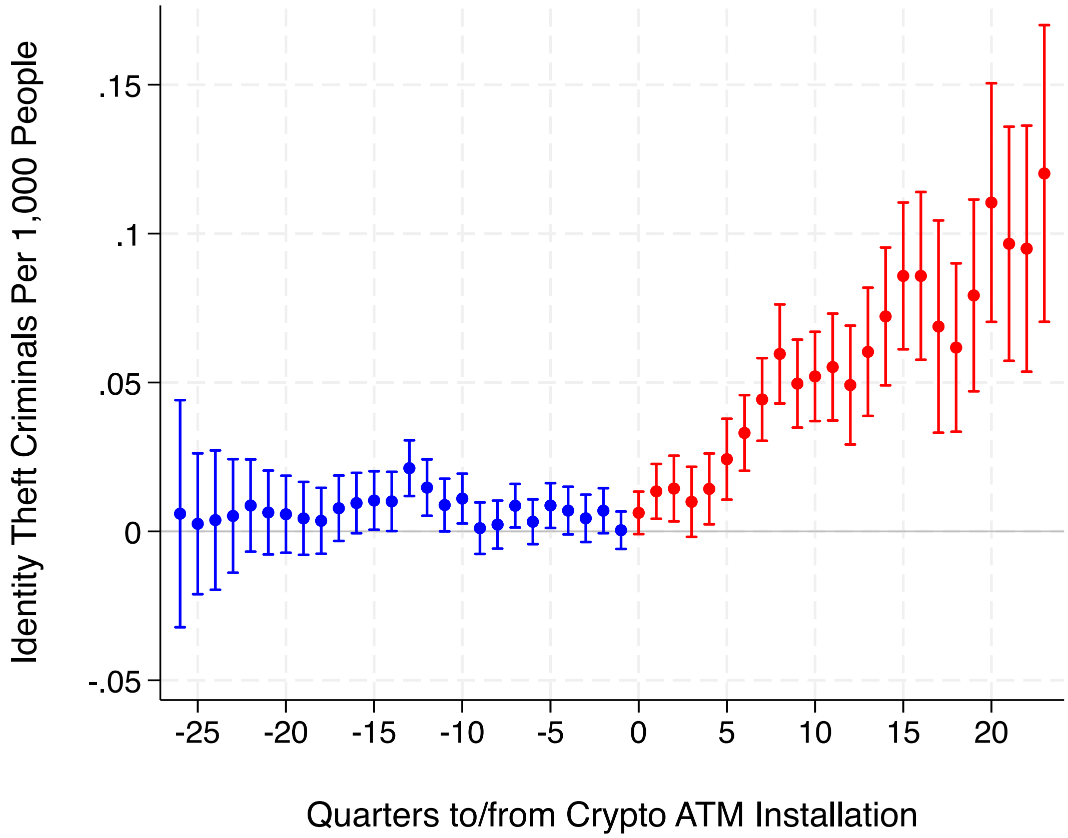


Figure A6: The Dynamic Impact of Crypto ATMs Installation on Regional Criminal Reports for Identity Theft Behaviors With Additional Specification: Callaway Sant'Anna Estimator

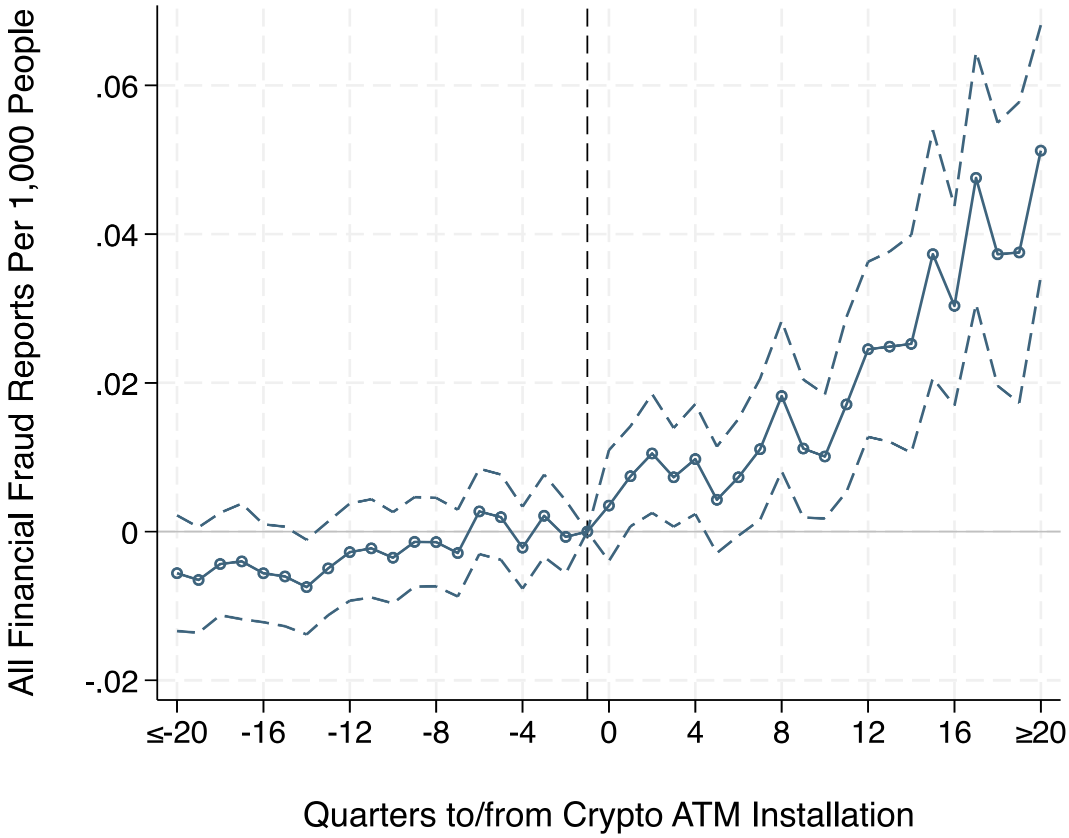


Figure A7: The Dynamic Impact of Crypto ATMs Installation on Regional Financial Fraud Reports: All Financial Fraud Reports

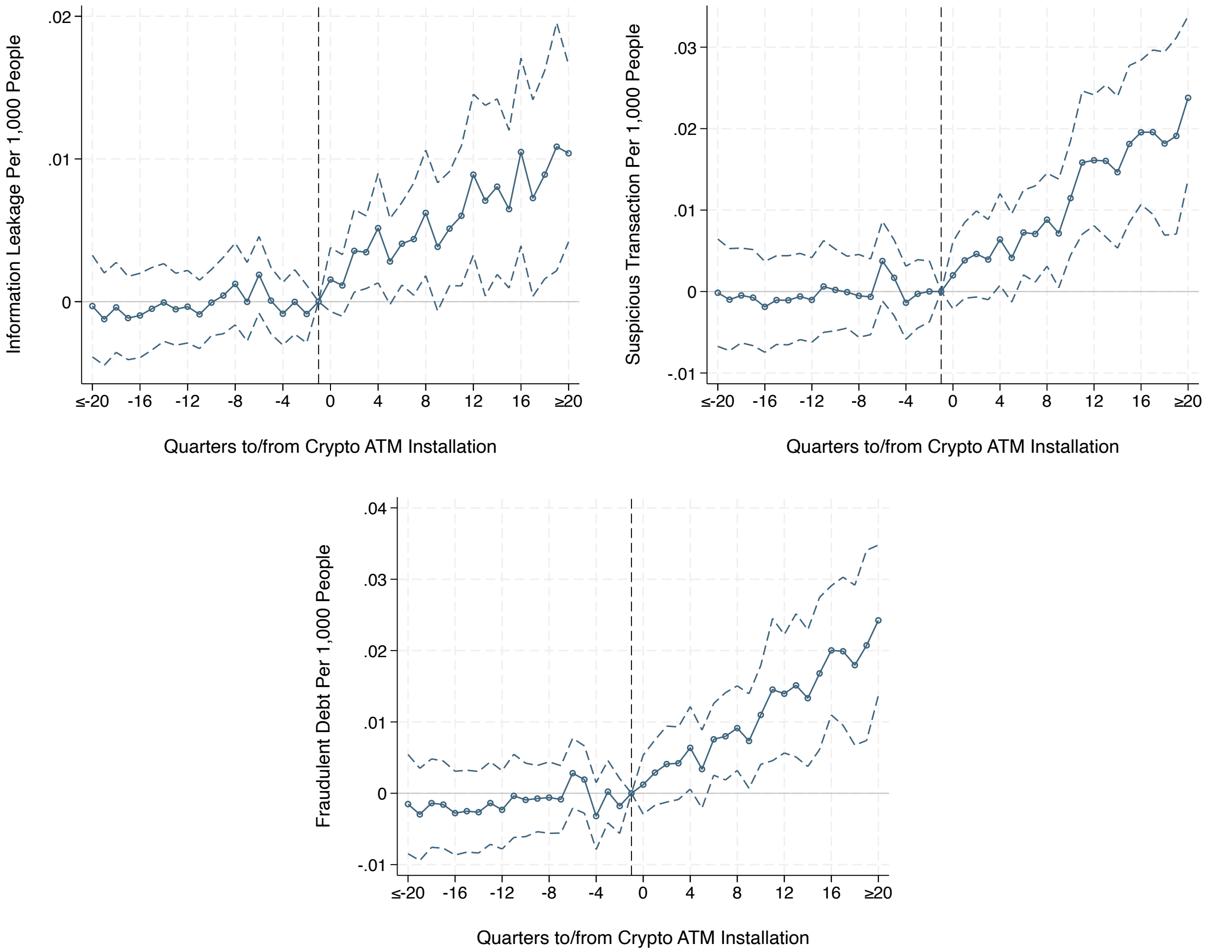


Figure A8: The Dynamic Impact of Crypto ATMs Installation on Regional Financial Fraud Reports: Alternative Specification Treated Only

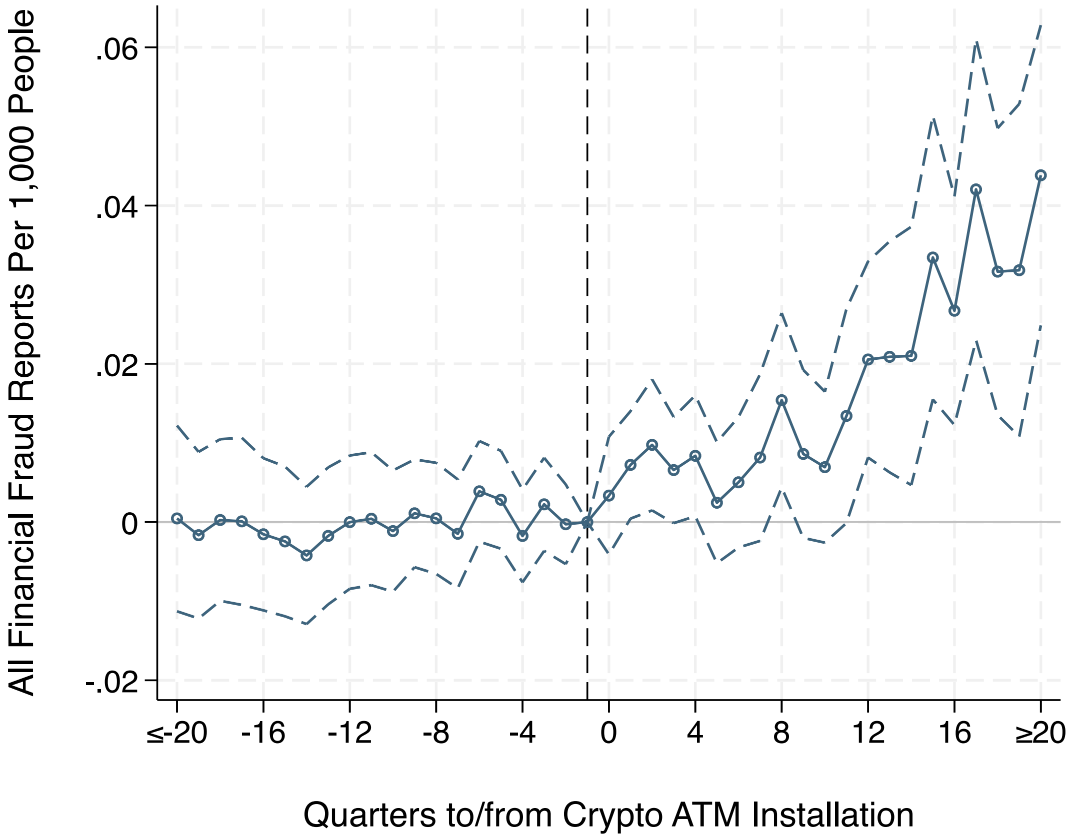


Figure A9: The Dynamic Impact of Crypto ATMs Installation on Regional Financial Fraud Reports: All Financial Fraud Reports, Alternative Specification Treated Only

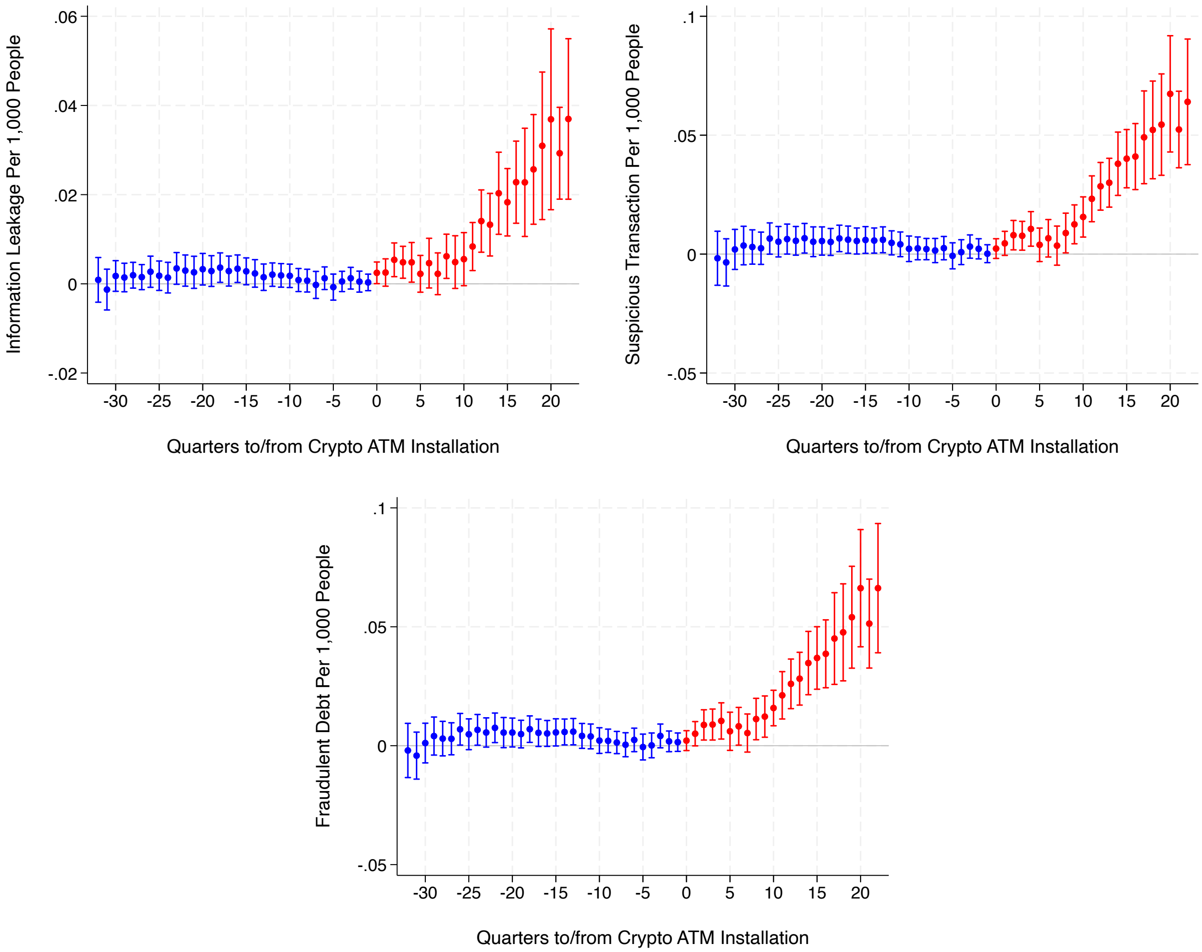


Figure A10: The Dynamic Impact of Crypto ATMs Installation on Regional Financial Fraud Reports With Additional Specification: Callaway Sant'Anna Estimator

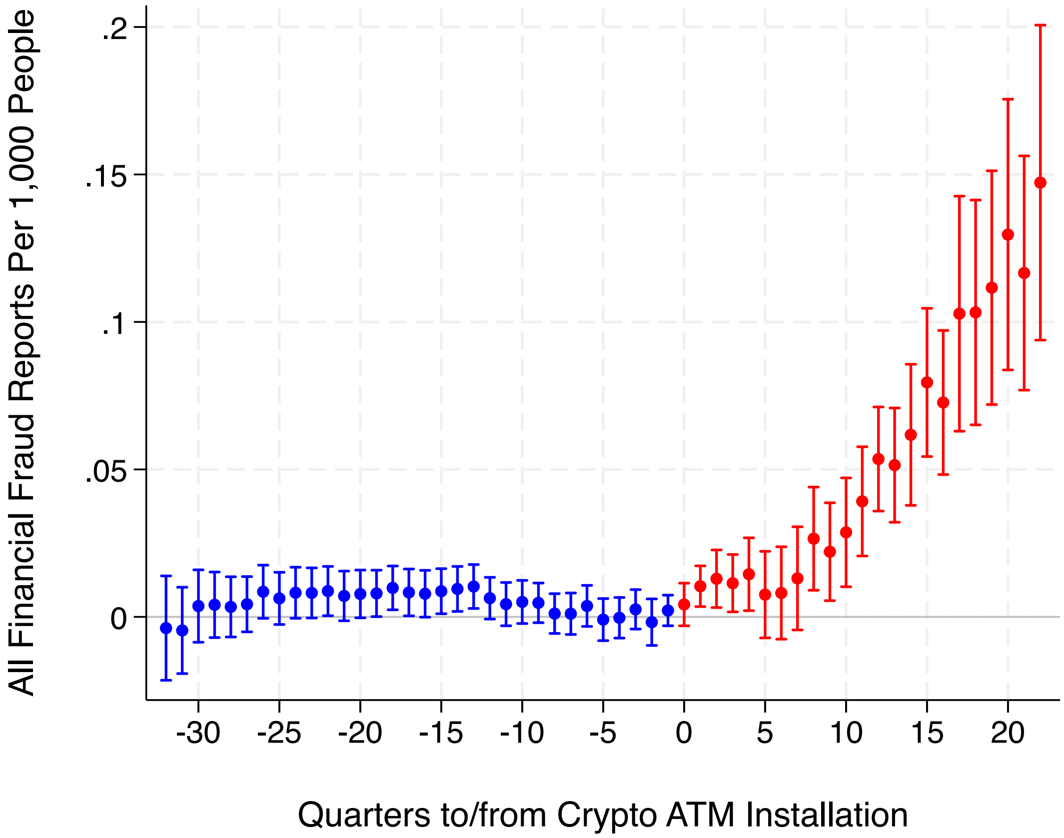


Figure A11: The Dynamic Impact of Crypto ATMs Installation on Regional Financial Fraud Reports: All Financial Fraud Reports, Callaway Sant'Anna Estimator

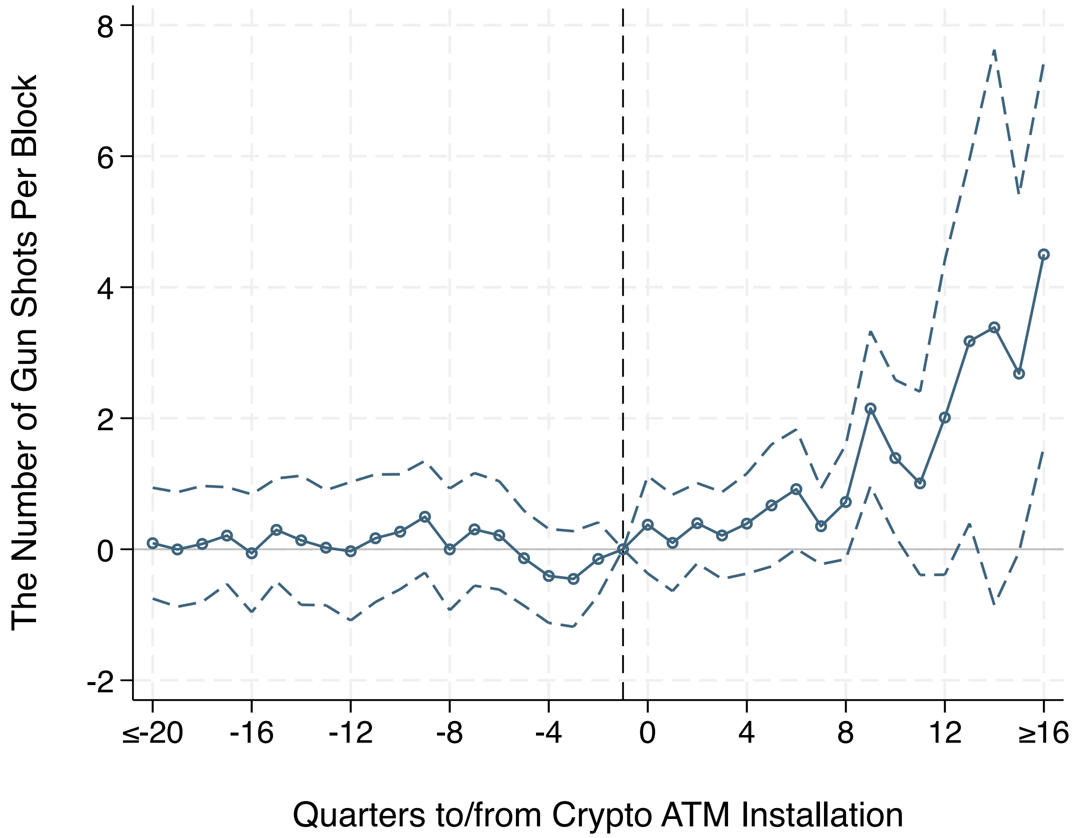


Figure A12: Crypto ATMs and Illegal Activities: Case Study from Minneapolis Gun Shots

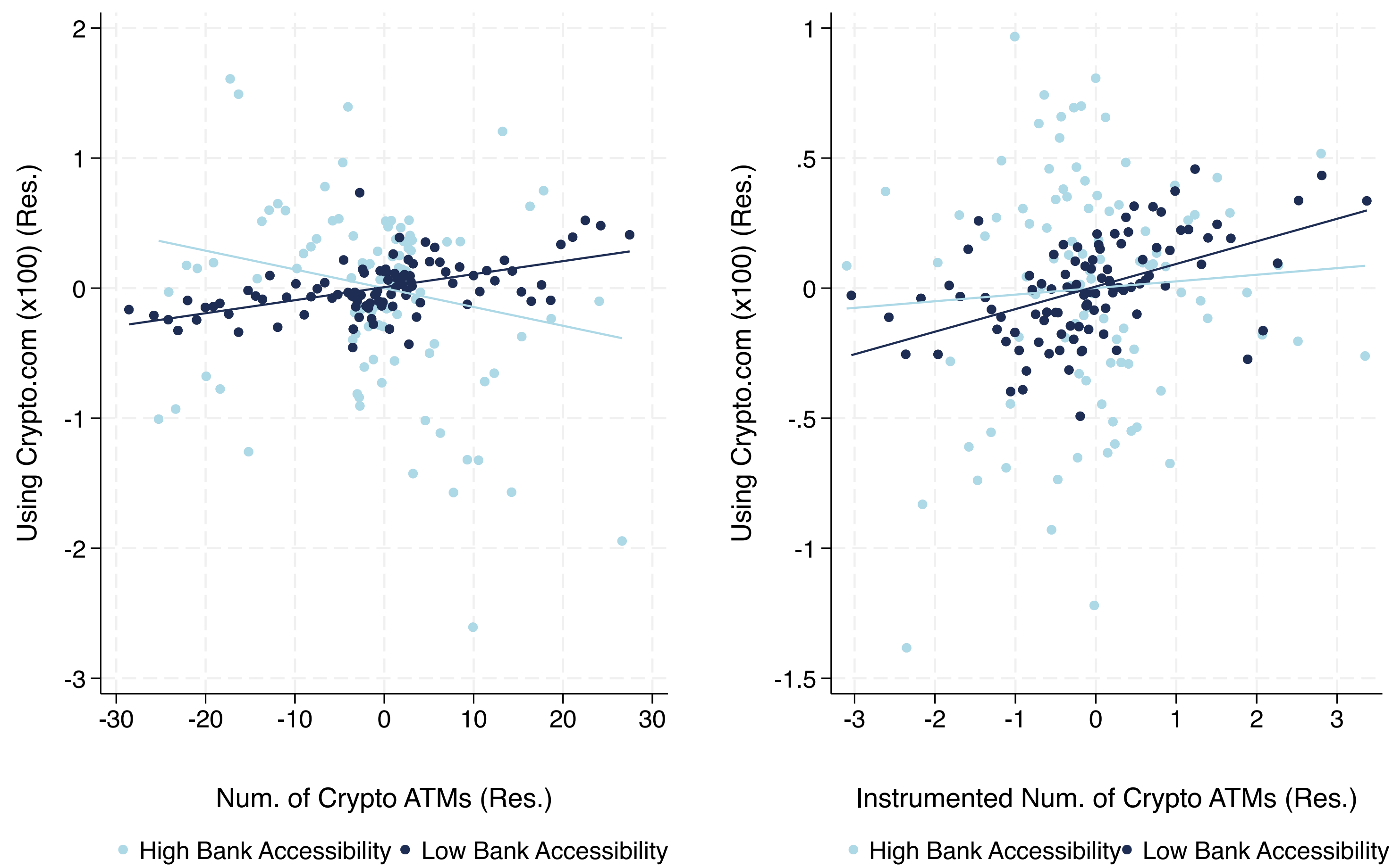


Figure A13: Differential Effects of Instrumented Number of Crypto ATMs by Accessibility to Banks: The Usage of *Crypto.Com* App

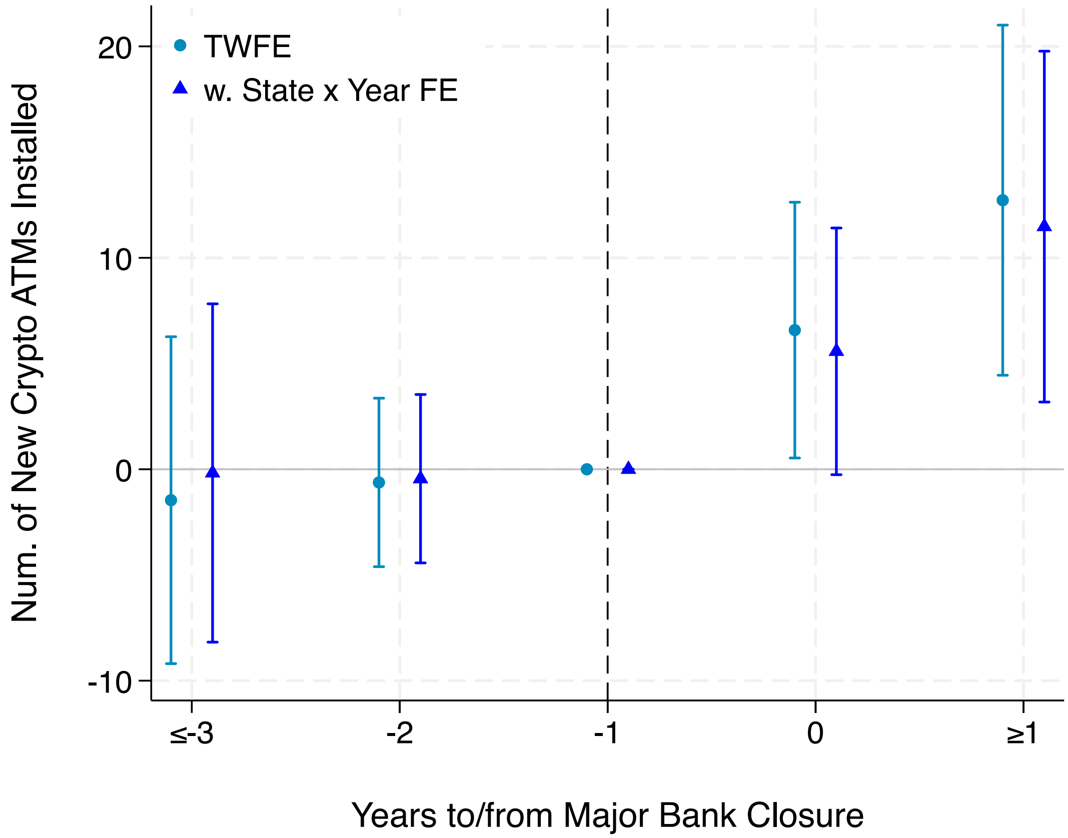


Figure A14: Assessing Mechanism: The Impact of Major Bank Closure Event on Crypto ATMs' Installation

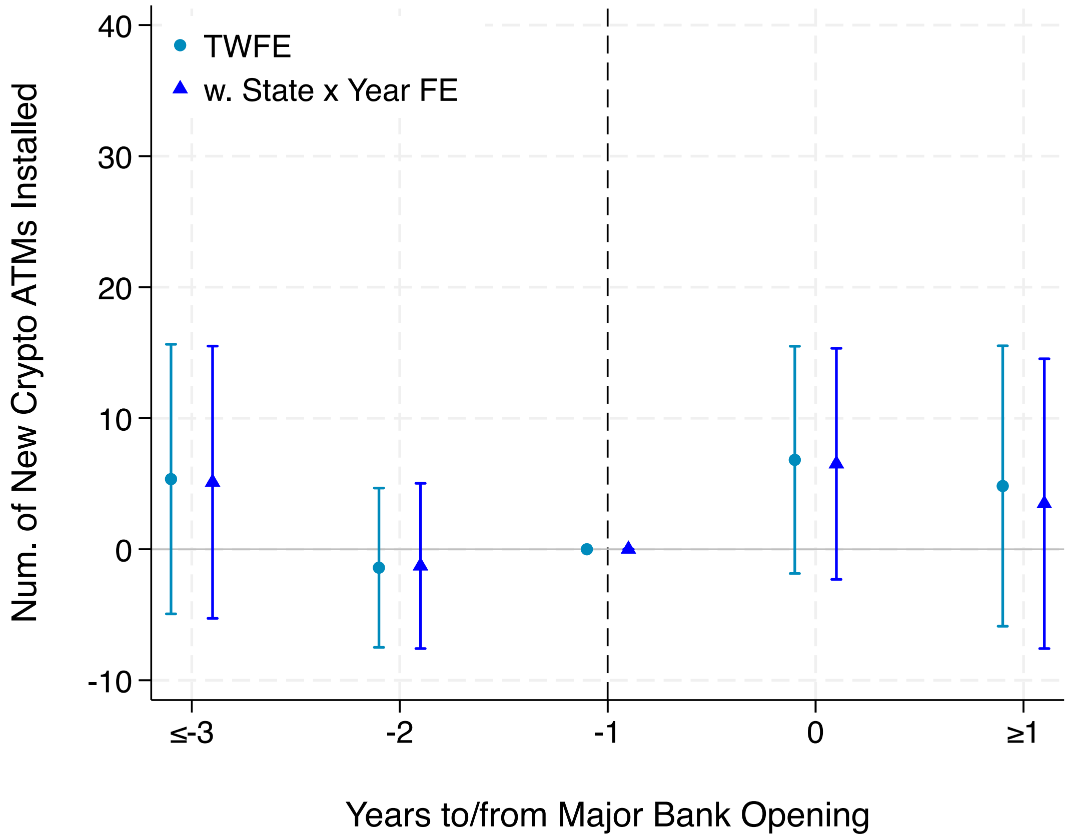


Figure A15: The Impact of Major Bank Opening Event on Crypto ATMs' Installation

Table A1: The Expansion of Crypto ATMs

Year	Num. of Zipcodes with Crypto ATMs	Total Num. of Crypto ATMs	Pop. With Access to Crypto ATMs (in Mil.)
2013	0	0	0.00
2014	69	74	0.82
2015	156	170	2.32
2016	416	501	5.94
2017	845	1,076	11.84
2018	1,459	1,982	19.90
2019	2,350	3,618	30.69
2020	4,894	9,914	56.59
2021	8,433	26,484	83.52
2022	9,312	32,734	93.41

Note: This table presents the summary statistics of how crypto ATMs are installed within the United States over the past decades. For each year, we present the total number of zip codes with at least one crypto ATMs installed, the total number of crypto ATMs, as well as the total population with access to crypto ATMs calculated by the number of population living in the zip code with at least one crypto ATM.

Table A2: Summary of the Consumer Reports

Panel A: Summary of Complaints for Financial Fraud-Related Suspicious Activity

Category	Num. of Complaints	Proportion of Complaints
Total Number of Financial Fraud-Related Complaints	149,649	100.00%
[Classified by Categories of Financial Fraud]		
... of Information Leakage	24,963	16.68%
... of Suspicious Transaction	85,887	57.39%
... of Fraudulent Debt	93,952	62.78%
[Classified by Complained Firms]		
... of Banks & Traditional Financial Service	38,713	25.87%
... of Investment & Asset Management	4,874	3.26%
... of Online Loan	67,556	45.14%
... of Financial Technology	2,622	1.75%
... of Credit Scoring	28,907	19.32%

Panel B: Summary of Complaints for Other Irregular Activity Not Related to Financial Crimes

Category	Num. of Complaints	Proportion of Complaints
Total Number of Other Irregular Financial Reports	268,426	100.00%
[Classified by Categories of Reported Issues]		
... of "Incorrect Information"	120,916	45.05%
... of "Incorrect Operations"	41,691	15.53%
... of Other Issues	105,819	39.42%

Note: This table presents summary statistics for the consumer reports collected for our empirical analysis. Panel A reports summary statistics for complaints related to financial fraud, while Panel B presents statistics for other complaints concerning irregular activities. We report both the total number of cases and the proportion of each type of report.

Table A3: Persistence of Shares Proxied by Loan Issuance

	Share of Bank Loans			
	(1)	(2)	(3)	(4)
Lag Share of Bank Loan	0.8450***	0.8308***	0.8531***	0.8426***
	(0.0001)	(0.0001)	(0.0002)	(0.0002)
Sample	Full	Full	2019-2022	2019-2022
County of the Bank FE		Yes		Yes
County of Loan FE		Yes		Yes
Year FE	Yes	Yes	Yes	Yes
N	17,895,080	17,895,080	7,158,032	7,158,032

Note: This table presents the persistence of bank loan shares between counties. Significance: * 10%; ** 5%; *** 1%.

Table A4: Pre-Trend Analysis of Shift-Share Instrumental Variable

	Shift-Share Instrument for Num. of ATMs at $t+\tau$		
	(1) $\tau = 1$	(2) $\tau = 2$	(3) $\tau = 3$
Employment (Standardized)	0.000521	0.000422	0.000348
	(0.0004)	(0.0004)	(0.0003)
Wage (Standardized)	0.001621	0.001305	0.001104
	(0.0014)	(0.0012)	(0.0010)
Population Growth	0.000175	0.000174	0.000163
	(0.0002)	(0.0002)	(0.0002)
Incorrect Info Report	−0.000568	−0.000278	0.000071
	(0.0028)	(0.0026)	(0.0023)
Incorrect Operation Report	0.000505	0.000537	0.000420
	(0.0005)	(0.0005)	(0.0004)
Other Financial Issue Report	0.000476	0.000134	−0.000152
	(0.0005)	(0.0004)	(0.0003)
New Bank Account	0.002519	−0.000312	−0.001707
	(0.0019)	(0.0010)	(0.0013)
Small Business Loan	0.009191	0.004300	−0.001663
	(0.0206)	(0.0201)	(0.0186)
Overdose Caused Deaths	−0.000086	−0.000076	−0.000056
	(0.0001)	(0.0001)	(0.0001)

Note: This table presents the estimation of the impact of crypto ATM installation on regional financial fraud reports, using OLS regression on county-level data. The regression model is $Outcome_{ct} = \beta Num\widehat{Crypto}ATMs_{ct+\tau} + Control + County\ FE + Year\text{-}Quarter\ FE + \varepsilon_{ct}$. We run this regression on the subsample where no crypto ATMs are installed. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A5: First-Stage Regression of Shift-Share Instrument Variable Estimation for the Number of Crypto ATMs

	Num. of Crypto ATMs
	(1)
Shift-Share Instrument for Num. of ATMs	0.1192***
	(0.0129)
R^2	0.738
F-score	85
County FE	Yes
Year-Quarter FE	Yes
N	84,520

Note: This table presents our first stage of our Shift-Share instrument variable estimation. Significance: * 10%; ** 5%; *** 1%.

Table A6: First-Stage Regression of Shift-Share Instrument Variable Estimation for the Number of Crypto ATMs (Without the Highest Connected Counties When Constructing the Shift-Share Instrument Variable)

	Num. of Crypto ATMs
	(1)
Shift-Share Instrument for Num. of ATMs	0.0711***
	(0.0068)
R^2	0.769
F-score	109
County FE	Yes
Year-Quarter FE	Yes
N	84,520

Note: This table presents our first stage of our Shift-Share instrument variable estimation but without the highest connected county when constructing the instrument variable. Significance: * 10%; ** 5%; *** 1%.

Table A7: First-Stage Regression of Instrument Variable Estimation for the Number of Crypto ATMs, Street-Density Times Bitcoin Price as the Instrument

	Num. of Crypto ATMs
	(1)
Street Density (2011) Times Bitcoin Price	0.1257***
	(0.0049)
R^2	0.805
F-score	666
County FE	Yes
Year-Quarter FE	Yes
N	84,520

Note: This table presents our first stage of our instrument variable estimation. Our instrumental variable is the street density of 2011 times the bitcoin price. Significance: * 10%; ** 5%; *** 1%.

Table A8: Robustness Checks: Instrumented Variable Approach Within the Sub-Sample with No Crypto ATMs

	Using Crypto Apps (×100)				
	(1)	(2)	(3)	(4)	(5)
Instrumented Num. of Crypto ATMs	0.1450	0.0391	0.0851	0.1057	−0.0063
	(0.1262)	(0.1182)	(0.1226)	(0.1214)	(0.0479)
R^2	0.060	0.060	0.061	0.126	0.657
County FE	Yes	Yes	Yes		
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Control		Yes	Yes	Yes	Yes
State FE × Bitcoin Price			Yes	Yes	Yes
Zip Code FE				Yes	
Individual FE					Yes
Mean of D.V.	5.67	5.67	5.67	5.67	5.67
N	231,497	231,482	231,482	229,948	166,331

Note: This table shows the robustness checks for impact of crypto ATM installation on individuals' decision to engage in the crypto market. We use Bartik-Instrument Variable strategy to estimate such impact, as shown in Table 2 but on the subsample with no crypto ATMs installed for a given county-quarter observation. The baseline regression model is: $EngageCrypto_{czit} = \beta \widehat{NumCryptoATMs}_{ct} + Year\text{-}Quarter\ FE + County\ FE + Control + \varepsilon_{czit}$, in which $EngageCrypto_{czit}$ equals one if individual i in zipcode z of county c uses crypto-related apps within year-quarter t and zero otherwise. $\widehat{NumCryptoATMs}$ is the Shift-Share instrumental variable predicted number of crypto ATMs. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A9: Robustness Checks: Excluding the Highest Weight When Constructing Shift-Share Instrumental Variable

	Using Crypto Apps (×100)				
	(1)	(2)	(3)	(4)	(5)
Instrumented Num. of Crypto ATMs	0.1814**	0.1460**	0.1492**	0.1444*	0.0375
	(0.0711)	(0.0739)	(0.0750)	(0.0758)	(0.0945)
R^2	0.038	0.038	0.038	0.081	0.647
County FE	Yes	Yes	Yes		Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Control		Yes	Yes	Yes	Yes
State FE × Bitcoin Price			Yes	Yes	Yes
Zip Code FE				Yes	
Individual FE					Yes

Note: This table shows the robustness checks on the impact of crypto ATM installation. We replicate Table 2, but with the instrumental variable calculated without the highest connected counties. To be specific, we report the second-stage regression coefficients of the IV approach. The baseline regression model in Panel B is: $EngageCrypto_{czit} = \beta Num\widehat{CryptoATMs}_{ct} + Year\text{-}Quarter\ FE + County\ FE + Control + \varepsilon_{czit}$, in which $EngageCrypto_{czit}$ equals one if individual i in zipcode z of county c uses crypto-related apps within year-quarter t and zero otherwise. $Num\widehat{CryptoATMs}_{ct}$ is the Shift-Share instrumental variable predicted number of crypto ATMs for county c of year-quarter t. We report the first-stage regression at Appendix Table A6. The baseline model includes a full set of county and time fixed effects, as well as macroeconomic control variables, including population, income, and total number of employment. We additionally provide the estimated coefficients with other fixed effects, such as state fixed effects times bitcoin price, zip code fixed effects, or individual fixed effects. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A10: Robustness Checks: Crypto ATMs and Crypto Market Engagement Alternative Instrumental Variable Street Density Times Bitcoin Price

	Using Crypto Apps (×100)				
	(1)	(2)	(3)	(4)	(5)
Instrumented Num. of Crypto ATMs	0.0500***	0.0413***	0.0382***	0.0427***	−0.0024
	(0.0149)	(0.0149)	(0.0146)	(0.0142)	(0.0152)
R^2	0.038	0.038	0.038	0.081	0.647
County FE	Yes	Yes	Yes		Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Control		Yes	Yes	Yes	Yes
State FE × Bitcoin Price			Yes	Yes	Yes
Zip Code FE				Yes	
Individual FE					Yes

Note: This table shows the robustness checks on the impact of crypto ATM installation. We replicate Table 2, but with the instrumental variable calculated by street density of 2011 times the bitcoin price at the end of each year-quarter. To be specific, we report the second-stage regression coefficients of the IV approach. The baseline regression model in Panel B is: $EngageCrypto_{czit} = \beta \widehat{NumCryptoATMs}_{ct} + \textit{Year-Quarter FE} + \textit{County FE} + \textit{Control} + \varepsilon_{czit}$, in which $EngageCrypto_{czit}$ equals one if individual i in zipcode z of county c uses crypto-related apps within year-quarter t and zero otherwise. $\widehat{NumCryptoATMs}_{ct}$ is instrumental variable predicted number of crypto ATMs for county c of year-quarter t. We report the first-stage regression at Appendix Table A7. The baseline model includes a full set of county and time fixed effects, as well as macroeconomic control variables, including population, income, and total number of employment. We additionally provide the estimated coefficients with other fixed effects, such as state fixed effects times bitcoin price, zip code fixed effects, or individual fixed effects. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A11: Additional Estimation for Crypto ATMs and Crypto Market Engagement: OLS Estimation

	Using Crypto Apps (×100)				
	(1)	(2)	(3)	(4)	(5)
Num. of Crypto ATMs	0.0204***	0.0217***	0.0203***	0.0207***	0.0129***
	(0.0053)	(0.0052)	(0.0049)	(0.0049)	(0.0045)
R^2	0.038	0.038	0.038	0.081	0.645
County FE	Yes	Yes	Yes		
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Control		Yes	Yes	Yes	Yes
State FE × Bitcoin Price			Yes	Yes	Yes
Zip Code FE				Yes	
Individual FE					Yes

Note: This table shows the impact of crypto ATM installation on individuals' decision to engage in the crypto market, estimated by OLS regression. The independent variable is the total number of crypto ATMs for a given county-quarter. The baseline model includes a full set of county and time fixed effects, as well as macroeconomic control variables, including population, income, and total number of employment. We additionally provide the estimated coefficients with other fixed effects, such as zip code fixed effects or individual fixed effects. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A12: Extensive Margin: Crypto ATMs and Crypto Market Engagement with Shift-Share Instrumental Variable Approach

	Minutes of Using Crypto Apps				
	(1)	(2)	(3)	(4)	(5)
Instrumented Num. of Crypto ATMs	0.3938**	0.3720*	0.4765***	0.4335***	0.4350
	(0.1850)	(0.2010)	(0.1768)	(0.1632)	(0.4897)
R^2	0.036	0.036	0.037	0.082	0.670
Mean of D.V.	5.86	5.86	5.86	5.86	5.86
County FE	Yes	Yes	Yes		Yes
Year-Quarter FE	Yes	Yes	Yes	Yes	Yes
Control		Yes	Yes	Yes	Yes
State FE × Bitcoin Price			Yes	Yes	Yes
Zip Code FE				Yes	
Individual FE					Yes

Note: This table presents the impact of crypto ATM installation on individuals' decisions to engage in the crypto market by analyzing the extensive margin of such effects. We use Bartik-style instrumental variable with two-stage least square (2SLS) approach to estimate the coefficients. To be specific, we report the second-stage regression coefficients of the IV approach. The baseline regression model is: $MinutesEngageCrypto_{czit} = \beta Num\widehat{CryptoATMs}_{ct} + Year\text{-}Quarter\ FE + County\ FE + Control + \varepsilon_{czit}$, in which $MinutesEngageCrypto_{czit}$ is the minutes of crypto-related app engagement of individual i in zipcode z in county c of quarter q. $Num\widehat{CryptoATMs}_{ct}$ is the Shift-Share instrumental variable predicted number of crypto ATMs for county c of year-quarter t. We report the first-stage regression at Appendix Table A5. The baseline model includes a full set of county and time fixed effects, as well as macroeconomic control variables, including population, income, and total number of employment. We additionally provide the estimated coefficients with other fixed effects, such as state fixed effects times bitcoin price, zip code fixed effects, or individual fixed effects. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A13: How Do People Engage in the Cryptocurrency Market? Heterogeneity by Different Crypto-Related Apps

	Instrumented Num. of Crypto ATMs		
Using Crypto Apps (× 100)	Coef.	S.E.	Mean of D.V.
Multi-Service Cryptocurrency Platform (Decentralized Payment & Credit Services)			
Crypto.com	0.0911***	(0.0271)	2.28
Centralized Exchange	0.0591	(0.0534)	6.74
Coinbase	0.0584	(0.0496)	5.96
Binance	−0.0102	(0.0066)	0.24
Crypto-Related News/Information			
CoinMarketCap	0.0100	(0.0071)	0.16
Other (Small) Crypto Platforms	0.0101**	(0.0039)	0.11

Note: This table presents the impact of crypto ATM installation on individuals' decisions to engage in the crypto market. We replicate the strategy in Table 2 by replacing the dependent variable with dummies of each kind of apps. We only report the regression coefficients for the instrumented number of crypto ATMs per county. The sample period is from 2019 to 2022, totaling 16 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A14: Robustness Checks: Crypto ATMs and Financial Frauds Consumer Reports Controlling for State FE Times Bitcoin Price

	Reported Financial Fraud Per 1,000 Capita		
	(1) Information Leakage	(2) Suspicious Transaction	(3) Fraudulent Debt
Instrumented Num. of Crypto ATMs	0.000211**	0.000632***	0.000342
	(0.0001)	(0.0002)	(0.0002)
R^2	0.212	0.312	0.316
Control	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
State FE × Bitcoin Price	Yes	Yes	Yes
Mean of D.V.	0.0062	0.0200	0.0211
N	84,512	84,512	84,512

Note: This table presents the robustness checks by including state × bitcoin price FE for the IV estimation of Table 7. The baseline regression model is $FinFraudRate_{ct} = \beta Num\widehat{CryptoATMs}_{ct} + Control + County\ FE + Year\text{-}Quarter\ FE + State\ FE \times Bitcoin\ Price + \varepsilon_{ct}$, in which $Num\widehat{CryptoATMs}$ is the Shift-Share instrumented number of crypto ATMs. Compared with our baseline, we additionally control for the state fixed effect times bitcoin price in our regression. *FinFraudRate* is calculated as the total number of financial fraud reports per 1,000 capita. The first stage regression is reported in Appendix Table A5. We include a full set of county-level and time fixed effects in our regression, as well as macroeconomic control variables including population, income, and total number of employments. The sample period is from 2013 to 2022, totaling 40 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A15: Robustness Checks: Crypto ATMs and Financial Frauds Consumer Reports Dropping the Highest Connected Counties When Constructing the Instrumental Variables

	Reported Financial Fraud Per 1,000 Capita		
	(1) Information Leakage	(2) Suspicious Transaction	(3) Fraudulent Debt
Instrumented Num. of Crypto ATMs	0.000394***	0.001064***	0.001000***
	(0.0001)	(0.0003)	(0.0003)
R^2	0.201	0.300	0.305
Control	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Mean of D.V.	0.0062	0.0200	0.0211
N	84,512	84,512	84,512

Note: This table presents the robustness checks by including state × bitcoin price FE for the IV estimation of Table 7. The baseline regression model is $FinFraudRate_{ct} = \beta Num\widehat{CryptoATMs}_{ct} + Control + County\ FE + Year\text{-}Quarter\ FE + State\ FE \times Bitcoin\ Price + \varepsilon_{ct}$, in which $Num\widehat{CryptoATMs}$ is the Shift-Share instrumented number of crypto ATMs. Compared with our baseline, we additionally control for the state fixed effect times bitcoin price in our regression. *FinFraudRate* is calculated as the total number of financial fraud reports per 1,000 capita. The first stage regression is reported in Appendix Table A5. We include a full set of county-level and time fixed effects in our regression, as well as macroeconomic control variables including population, income, and total number of employments. The sample period is from 2013 to 2022, totaling 40 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A16: Robustness Checks: Crypto ATMs and Financial Frauds Consumer Reports Alternative Instrumental Variable Street Density Times Bitcoin Price

	Reported Financial Fraud Per 1,000 Capita		
	(1) Information Leakage	(2) Suspicious Transaction	(3) Fraudulent Debt
Instrumented Num. of Crypto ATMs	0.000326***	0.000542***	0.000525***
	(0.0001)	(0.0001)	(0.0001)
R^2	0.337	0.443	0.455
Control	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Mean of D.V.	0.0062	0.0200	0.0211
N	84,512	84,512	84,512

Note: This table presents the robustness checks by using street density of 2011 times bitcoin price as the instrument in the estimation of Table 7. The baseline regression model is $FinFraudRate_{ct} = \beta Num\widehat{CryptoATMs}_{ct} + Control + County\ FE + Year\text{-}Quarter\ FE + \varepsilon_{ct}$, in which $Num\widehat{CryptoATMs}$ is the instrumented number of crypto ATMs by street density times bitcoin price. *FinFraudRate* is calculated as the total number of financial fraud reports per 1,000 capita. The first stage regression is reported in Appendix Table A7. We include a full set of county-level and time fixed effects in our regression, as well as macroeconomic control variables including population, income, and total number of employments. The sample period is from 2013 to 2022, totaling 40 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A17: Crypto ATMs and Financial Frauds Consumer Reports: County-Level OLS Estimation

	Reported Financial Fraud Per 1,000 Capita		
	(1) Information Leakage	(2) Suspicious Transaction	(3) Fraudulent Debt
Num. of Crypto ATMs	0.000179***	0.000436***	0.000407***
	(0.0000)	(0.0001)	(0.0001)
R^2	0.203	0.303	0.307
Control	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
N	84,512	84,512	84,512

Note: This table presents the estimation of the impact of crypto ATM installation on regional financial fraud reports, using OLS regression on county-level data. The regression model is $FinFraudRate_{ct} = \beta NumCryptoATMs_{ct} + Control + County\ FE + Year\text{-}Quarter\ FE + \varepsilon_{ct}$, in which *NumCryptoATMs* is the number of crypto ATMs. *FinFraudRate* is calculated as the total number of financial fraud reports per 1,000 capita. The sample period is from 2013 to 2022, totaling 40 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A18: Crypto ATMs and Financial Frauds Consumer Reports: All Consumer Reports

	Reported Total Financial Fraud Per 1,000 Capita		
	(1)	(2)	(3)
Panel A: County-Level Instrumental Variable Estimation			
Instrumented Num. of Crypto ATMs	0.002518***	0.001275***	0.001410***
	(0.0005)	(0.0005)	(0.0005)
R^2	0.363	0.380	0.397
County FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
Control		Yes	Yes
State FE × Bitcoin Price			Yes
Mean of D.V.	0.0355	0.0355	0.0355
N	84,512	84,512	84,512
Panel B: Zip Code-Level Difference-in-Difference Estimation			
Post Crypto ATM Installation		0.007882***	0.005023**
		(0.0020)	(0.0020)
R^2		0.369	0.372
Control			Yes
Zip Code FE		Yes	Yes
County × Year-Quarter FE		Yes	Yes
Mean of D.V.		0.0754	0.0754
N		279,724	279,724

Note: This table presents the estimation of the impact of crypto ATM installation on all regional financial fraud reports among three categories. The event study extension of the DiD estimation of Panel B is in Appendix Figure A7. The sample period is from 2013 to 2022, totaling 40 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A19: Crypto ATM and Irregular Reports Unrelated to Financial Frauds or Crimes

	Inquiries Per 1,000 Capita		
	(1) Incorrect Information	(2) Incorrect Operation	(3) Others
Panel A: County-Level Instrumental Variable Estimation			
Instrumented Num. of Crypto ATMs	0.000492	0.000575	0.000317
	(0.0022)	(0.0004)	(0.0003)
R^2	0.268	0.174	0.171
Sample	Full	Full	Full
Control	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes
N	84,510	84,510	84,510
Panel B: Zip Code-Level Difference-in-Difference Estimation			
Post Crypto ATM Installation	0.010446**	0.003202**	0.002294**
	(0.0052)	(0.0013)	(0.0010)
R^2	0.567	0.384	0.217
Sample	Full	Full	Full
Control	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes
County × Year-Quarter FE	Yes	Yes	Yes
N	305,708	305,708	305,708

Note: This table presents instrumental variable estimation of the impact of crypto ATM installation on other finance-related consumer reports unrelated to financial criminal behaviors. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A20: Heterogeneity by Accessibility to Banking System OLS Estimation

Panel A: Crypto Market Engagement

	Using the Apps (×100)		
	(1) All Crypto Apps	(2) *Crypto.com*	(3) Central Crypto Exchange
Num. of Crypto ATMs	−0.0350**	−0.0144**	−0.0277**
× Banks Per Capita (Standardized)	(0.0150)	(0.0073)	(0.0139)
Num. of Crypto ATMs	−0.0454	−0.0326**	−0.0296
× High Bank Accessibility Dummy	(0.0361)	(0.0128)	(0.0342)

Panel B: Financial Fraud

	Reported Financial Fraud Per 1,000 Capita		
	(1) Information Leakage	(2) Suspicious Transaction	(3) Fraudulent Debt
Num. of Crypto ATMs	−0.000041	−0.000112*	−0.000100
× Banks Per Capita (Standardized)	(0.0000)	(0.0001)	(0.0001)
Num. of Crypto ATMs	−0.000067*	−0.000176**	−0.000181**
× High Bank Accessibility Dummy	(0.0000)	(0.0001)	(0.0001)
Num. of Crypto ATMs	Yes	Yes	Yes
Control	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes

Note: This table presents heterogeneous impact of crypto ATM installation by regional accessibility to commercial banks. The baseline regression model is $EngagingFinancialMarket_{czit} = \beta_1 NumCryptoATMs_{ct} \times BankAccess_c + \beta_2 NumCryptoATMs_{ct} + Control + County\ FE + Year\text{-}Quarter\ FE + \varepsilon_{ct}$. We include a full set of county-level and time fixed effects in our regression, as well as macroeconomic control variables including population, income, and total number of employments. The sample period is from 2013 to 2022, totaling 40 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A21: Heterogeneity by Accessibility to Banking System (Crypto Market Engagement): Individual-Level Difference-in-Differences

	Using Crypto Apps (×100)				
	(1)	(2)	(3)	(4)	(5)
Panel A: Number of Banks					
All Crypto Apps					
Post Crypto ATM Installation	−1.0433**	−1.0436**	−0.4336*	−0.2926	−0.0821
× Number of Banks	(0.4350)	(0.4349)	(0.2469)	(0.2359)	(0.2650)
Crypto.com					
Post Crypto ATM Installation	−0.5051**	−0.4991**	−0.2333*	−0.0915	−0.0232
× Number of Banks	(0.2099)	(0.2091)	(0.1404)	(0.1389)	(0.1695)
Centralized Cryptocurrency Exchange					
Post Crypto ATM Installation	−0.8469**	−0.8491**	−0.2959	−0.2121	−0.0234
× Number of Banks	(0.4186)	(0.4188)	(0.2443)	(0.2364)	(0.2606)
Panel B: Dummy for Banks					
All Crypto Apps					
Post Crypto ATM Installation	−1.5858***	−1.5845***	−0.5319	−0.3100	−0.0906
× Number of Banks > 0	(0.6074)	(0.6043)	(0.4073)	(0.3972)	(0.4864)
Crypto.com					
Post Crypto ATM Installation	−0.9060***	−0.8978***	−0.4848*	−0.2687	−0.1228
× Number of Banks > 0	(0.3168)	(0.3160)	(0.2503)	(0.2521)	(0.3219)
Centralized Cryptocurrency Exchange					
Post Crypto ATM Installation	−1.1415**	−1.1435**	−0.2278	−0.1020	0.0244
× Number of Banks > 0	(0.5706)	(0.5674)	(0.3928)	(0.3869)	(0.4618)
Post Crypto ATM Installation	Yes	Yes	Yes	Yes	Yes
Zip Code FE	Yes	Yes			
Year-Quarter FE	Yes	Yes	Yes		
Control		Yes	Yes	Yes	Yes
Individual FE			Yes	Yes	Yes
State × Year-Quarter FE				Yes	
County × Year-Quarter FE					Yes

Note: This table shows the heterogeneous impact of crypto ATM installation on individuals' decision to engage in the crypto market, by difference in accessibility in traditional banks. We interact the post-crypto ATM installation dummy with variables indicating the existence of banks, and included this variable in our difference-in-differences regression: $EngageCrypto_{czit} = \beta_1 PostCryptoATM_{it} + \beta_2 PostCryptoATM_{it} \times Bank + County \times Year\text{-}Quarter\ FE + Individual\ FE + Control + \varepsilon_{czit}$. For Panel A, the variables measuring the density of banks is the number of banks within a given zip code, and for Panel B, the variable is a dummy indicating whether any banks exist in the zip code. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A22: Heterogeneity by Accessibility to Banking System (financial fraud reports): Zip Code Level Difference-in-Differences

	Reported Financial Fraud Per 1,000 Capita		
	(1) Information Leakage	(2) Suspicious Transaction	(3) Fraudulent Debt
Panel A: Number of Banks			
Post Crypto ATM Installation	−0.001548*	−0.001666	−0.002287*
× Number of Banks	(0.0008)	(0.0012)	(0.0013)
Panel B: Dummy for Banks			
Post Crypto ATM Installation	−0.003138**	−0.004372*	−0.005369**
× Number of Banks > 0	(0.0013)	(0.0024)	(0.0025)
Post Crypto ATM Installation	Yes	Yes	Yes
Control	Yes	Yes	Yes
Zip Code FE	Yes	Yes	Yes
County × Year-Quarter FE	Yes	Yes	Yes

Note: This table presents the difference-in-differences estimation of the heterogeneous impact of crypto ATM installation on regional financial fraud reports, by the regional accessibility to the banking system. The baseline regression model is $FinFraudRate_{czt} = \beta_1 PostCryptoATM_{czt} + \beta_2 PostCryptoATM_{czt} \times Banks + Control + Zip\ Code\ FE + County \times Year\text{-}Quarter\ FE + \varepsilon_{czt}$. For Panel A, *Bank* is equal to the total number of banks within a given zip code, and for Panel B, it is a dummy indicating whether any banks exist in the zip code. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A23: Predicting the Number of Crypto ATMs with the Number of Banks: Pre-Trend Tests

	Number of New Crypto ATMs Installed				
	(1)	(2)	(3)	(4)	(5)
	τ =−1	τ =0	τ =1	τ = 2	τ =3
Number of Banks Closed at $t + \tau$	0.9007***	0.6701*	0.0990	0.1549	0.1947
	(0.2824)	(0.3746)	(0.4702)	(0.2511)	(0.1734)
Number of Banks Opened at $t + \tau$	−0.4557	−0.2556	−0.9606*	−0.5788	−0.3086*
	(0.7179)	(0.6635)	(0.5452)	(0.3916)	(0.1674)
Control	Yes	Yes	Yes	Yes	Yes
State × Year FE	Yes	Yes	Yes	Yes	Yes
County FE	Yes	Yes	Yes	Yes	Yes

Note: In this table, we present the estimated coefficient of Figure 6. We predict the number of new crypto ATMs installed using the lagged or lead number of bank closures/openings. We resample our data to annual frequency, as the number of banks is an annual data. We run the following regression: $NumNewCryptoATM_{ct} = \beta_1 NumBankClose_{ct+\tau} + \beta_2 NumBankOpen_{ct+\tau} + Control + State \times Year\ FE + County\ FE + \varepsilon_{ct}$, in which $NumBankClose_{ct+\tau}$ is the number of bank branches closed in county c of year $t + \tau$, and $NumBankOpen_{ct+\tau}$ is that of new banks open. The range of τ in our analysis is from −3 to 3, that is, we use "future" closed or opened banks to predict the number of new crypto ATMs installed in year t to test the pre-trend. We include state-year joint fixed effects to avoid the influence by state-level crypto and bank-related regulations. A full set of macroeconomic control, including population, income, and employment are included. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A24: Bank Closure and New Crypto ATMs Installed: Event Study on Major Bank Closure

	Num. of New Crypto ATMs Installed	
	(1)	(2)
Three Years or More Before	−1.4623	−0.1771
	(3.9442)	(4.0816)
Two Years Before	−0.6232	−0.4471
	(2.0327)	(2.0318)
Bank Closure Event	6.5808**	5.5764*
	(3.0859)	(2.9762)
One Year or Later	12.7249***	11.4755***
	(4.2243)	(4.2332)
Control	Yes	Yes
County FE	Yes	Yes
Year FE	Yes	
State × Year FE		Yes

Note: This table presents the event study estimation of the impact of major bank closure event on crypto ATMs' installation. We define the closure of at least 17 bank branches, approximately the 1% number of bank branch closure across all observations, as an event of major bank closure. The baseline regression model is $NumNewCryptoATM_{ct} = \sum_{t=T} \beta_T T_{it} + Control + State \times Year\ FE + County\ FE + \varepsilon_{ct}$, in which T_{it} is a set of dummies that indicate years before or since the major bank closure event. The coefficient is presented visually in Figure A14. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A25: Bank Open and New Crypto ATMs Installed: Event Study on Major Bank Opening

	Num. of New Crypto ATMs Installed	
	(1)	(2)
Three Years or More Before	5.3553	5.1149
	(5.2486)	(5.3010)
Two Years Before	−1.4084	−1.2717
	(3.1016)	(3.2175)
Bank Open Event	6.8213	6.5164
	(4.4248)	(4.4988)
One Year or Later	4.8261	3.4785
	(5.4588)	(5.6414)
Control	Yes	Yes
County FE	Yes	Yes
Year FE	Yes	
State × Year FE		Yes

Note: This table presents the event study estimation of the impact of major bank opening event on crypto ATMs' installation. We define the opening of at least 7 bank branches, approximately the 1% number of bank branch opening across all observations, as an event of major bank opening. The baseline regression model is $NumNewCryptoATM_{ct} = \sum_{t=T} \beta_T T_{it} + Control + State \times Year\ FE + County\ FE + \varepsilon_{ct}$, in which T_{it} is a set of dummies that indicate years before or since the major bank open event. The coefficient is presented visually in Appendix Figure A15. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A26: Heterogeneity by Other Regional Demographics: Financial Engagement

	Using the Apps (×100)		
	(1) All Crypto Apps	(2) *Crypto.com*	(3) Central Crypto Exchange
Panel A: Internet Access			
Instrumented Num. of Crypto ATMs	2.4995***	1.5066***	1.9745***
× Smartphone User Ratio	(0.4243)	(0.2483)	(0.3900)
Panel B: Race			
Instrumented Num. of Crypto ATMs	−0.1380	−0.1209	−0.1058
× Black Ratio	(0.1441)	(0.0980)	(0.1382)
Instrumented Num. of Crypto ATMs	0.3401**	0.1545**	0.2787**
× Latino Ratio	(0.1339)	(0.0770)	(0.1315)
Panel C: Educational Level			
Instrumented Num. of Crypto ATMs	−0.0059	−0.0653	0.0096
× Bachelors Ratio	(0.1250)	(0.0778)	(0.1184)
Panel D: Income			
Instrumented Num. of Crypto ATMs	−0.0415	−0.0597***	−0.0128
× Average Income (Standardized)	(0.0678)	(0.0216)	(0.0621)
Lower Order Interaction Terms	Yes	Yes	Yes
Control	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes

Note: This table presents heterogeneous impact of crypto ATM installation on regional financial engagements. We estimate 2SLS regression with Shift-Share instrumental variable on county-level regional financial fraud reports. We instrument the number of crypto ATMs as well as its interaction with demographic data by the shift-share instrument as well as the interaction term of SSIV with demographic data. The baseline regression model is $EngagingFinancialMarket_{czit} = \beta_2 Num\widehat{CryptoATMs}_{ct} \times Demographics_{ct} + \beta_2 Num\widehat{CryptoATMs}_{ct} + Control + County\ FE + Year\text{-}Quarter\ FE + \varepsilon_{ct}$. We include a full set of county-level and time fixed effects in our regression, as well as macroeconomic control variables including population, income, and total number of employments. We do not report the regression coefficients of lower order interaction terms of demographics or instrumented value of number of crypto ATMs, as they do not reflect the heterogeneous effects. The sample period is from 2013 to 2022, totaling 40 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A27: Heterogeneity by Other Regional Demographics: Financial Frauds

	Reported Financial Fraud Per 1,000 Capita		
	(1) Information Leakage	(2) Suspicious Transaction	(3) Fraudulent Debt
Panel A: Internet Access			
Instrumented Num. of Crypto ATMs × Smartphone User Ratio	0.003516***	0.007045***	0.005410**
	(0.0009)	(0.0021)	(0.0022)
Panel B: Race			
Instrumented Num. of Crypto ATMs × Black Ratio	0.003788***	0.007989***	0.008575***
	(0.0004)	(0.0007)	(0.0007)
Instrumented Num. of Crypto ATMs × Latino Ratio	0.000267	0.000852*	0.000496
	(0.0002)	(0.0005)	(0.0005)
Panel C: Educational Level			
Instrumented Num. of Crypto ATMs × Bachelors Degree Ratio	0.000325	0.000745*	0.000387
	(0.0002)	(0.0004)	(0.0005)
Panel D: Income			
Instrumented Num. of Crypto ATMs × Average Income (Standardized)	−0.000016	0.000031	0.000038
	(0.0000)	(0.0001)	(0.0001)
Lower Order Interaction Terms	Yes	Yes	Yes
Control	Yes	Yes	Yes
County FE	Yes	Yes	Yes
Year-Quarter FE	Yes	Yes	Yes

Note: This table presents the heterogeneous impact of crypto ATM installation on regional financial fraud reports by regional demographics. We gather county-level demographic data for our heterogeneous analysis. We estimate 2SLS regression with Shift-Share instrumental variable on county-level regional financial fraud reports. We instrument the number of crypto ATMs as well as its interaction with demographic dummies by the shift-share instrument as well as the interaction term of SSIV with demographic dummies. The baseline regression model is $FinFraudRate_{ct} = \beta_2 Num\widehat{CryptoATMs} \times Demographics_c + \beta_2 Num\widehat{CryptoATMs}_{ct} + Control + County\ FE + Year\text{-}Quarter\ FE + \varepsilon_{ct}$. We include a full set of county-level and time fixed effects in our regression, as well as macroeconomic control variables including population, income, and total number of employments. We do not report the regression coefficients of lower order interaction terms of demographics or instrumented value of number of crypto ATMs, as they do not reflect the heterogeneous effects. The sample period is from 2013 to 2022, totaling 40 year-quarters. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.

Table A28: Income Inequality: Crypto ATMs' Installation and Gini Coefficient

	Gini Coefficient	
	(1)	(2)
Instrumented Num. of Crypto ATMs	−0.000291**	−0.000248*
	(0.0001)	(0.0001)
Control		Yes
County FE	Yes	Yes
Year FE	Yes	Yes
N	21,159	21,158

Note: This table presents the impact of crypto ATMs' installation on regional inequality, proxied by annualized Gini coefficient per county. We run the following regression: $Gini_{ct} = \beta Num\widehat{Crypto}ATMs_{ct} + Control + County\ FE + Year\ FE + \varepsilon_{ct}$. The sample period is from 2013 to 2022, totaling 10 years. We cluster our standard-errors at the county level. Significance: * 10%; ** 5%; *** 1%.