

Competing Network Effects: Evidence from Crypto and Gambling Adoption*

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Abstract

We study the impact of peer effects on the adoption of new retail financial products such as cryptocurrencies and online gambling. Using transaction level data from PayPal and Venmo, we show a novel crowd-out effect within social networks - peers with divergent interests compete for the limited attention or time of their friends. Using exogenous shocks to the exposure of peers to cryptocurrencies and online gambling, we show that peers with interests in cryptocurrencies (gambling) amplify the adoption of crypto (gambling) among their peers, at the expense of the other activity. Therefore, “pre-existing” peer interests in one activity impede (and partially crowd out) the adoption of the other. We hypothesize that this is due to limited attention or resources on the part of peers.

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1 Introduction

A large literature in economics and finance highlights the role of peer effects in the adoption of new products, technologies, or services, as well as broader economic and financial outcomes; for examples in finance see Hong, Kubik, and Stein (2004), Hirshleifer (2020) or Kuchler and Stroebe (2021). Much less is known, however, about the mechanisms through which these peer effects interact or even compete with one another. Individuals typically belong to multiple, overlapping networks whose members may engage in a wide range of behaviors or choices. Although peers can reinforce the adoption of a particular technology, or product among their friends, different peers—or subsets of peers—may also promote competing activities that vie for an individual’s limited time, attention, and financial resources. In this paper, we shed light on this aspect of peer effects that has not been studied in the literature.

The specific application we analyze is the role of peer effects in the adoption of new digital financial products, in particular, cryptocurrencies and online gambling. These activities have seen rapid growth among U.S. retail investors over the past decade. They are often compared to each other, since these are risk-taking activities with a significant social network component. They also require financial and time commitment, as well as engagement with distinct platforms. For this analysis, we take a person’s peer network as given and study how shocks to a peer’s engagement in gambling or cryptocurrency trading transmit to their friends. Our results show that peers with interests in cryptocurrencies reinforce the adoption of crypto trading among their peers; and similarly for gambling. This positive amplification effect confirms what has previously been shown in the peer effects literature.

In addition, however, we document that “pre-existing” peer interest in one of these activities impedes (and partially crowds out) the adoption of the other activity. In other words, if a person’s peers already trade cryptocurrencies, the person is less likely to adopt gambling even when it becomes available (and similarly for gambling). These results suggest that people have limited time budgets or even financial resources for different activities and that peers across different types of activities compete for their friends’ attention to engage in like-minded activities. We also show that there is not a one-for-one crowd out of the money spent on gambling and cryptocurrency trading and thus peer exposure to these technologies leads to higher spending overall. But we do not find a reduction in spending on other purchases. This might suggest that competition in peer effects is strongest between activities that are close substitutes, but do not lead to a general crowding out.

The difficulty in studying these competing network effects lies in the significant data requirements and demands on the research design. First, we need to be able to map a person’s

peer networks and observe the competing or overlapping activities that the person and their friends engage in. Second, we need to observe (quasi) exogenous shocks to the adoption of different behaviors by peers to differentiate peer effects from assortative matching in peer networks, see for example Goldsmith-Pinkham and Imbens (2013) and Bramoullé, Djebbari, and Fortin (2020). To address these challenges, we use a unique network environment and data source: We obtained (anonymized) transaction level data from PayPal and Venmo, two of the largest digital payment systems in the US, both owned by the same parent company. PayPal data allows us to analyze cryptocurrency adoption among users, as PayPal was one of the first platforms that facilitated retail investments in cryptocurrencies (Bitcoin, Ethereum and BitcoinCash). We use Venmo data to trace online gambling adoption and spending, since Venmo has denser and more detailed data on peer-to-peer payments, making it better suited for studying social networks.¹ On both platforms users can send money to each other. We construct a measure of individuals’ social networks based on their “payment friends”, defined as peers with whom they have engaged in mutual peer-to-peer transactions, i.e. they have sent money in both directions within the relationship. This is a particularly demanding definition of a social connection as it involves engaging in actual financial transactions back and forth with a friend.

To analyze the role of payment friends in the adoption of cryptocurrencies and online gambling, we identify two different sources of (exogenous) variation in the data:

Cryptocurrency Experiment: The first is experimental variation in the exposure of different peers to cryptocurrencies. Shortly after enabling users to purchase cryptocurrencies on its PayPal platform in the fall of 2020, PayPal conducted several large-scale marketing experiments providing financial incentives to customers to purchase cryptocurrencies through PayPal.² We confirm that the marketing experiments had a positive impact on the adoption of cryptocurrencies. Users who (randomly) received incentives are more likely to adopt and trade cryptocurrencies. In addition, if a person has more friends that were already trading crypto currencies they are more likely to adopt. This result is suggestive, but the pre-existing interests of a person’s peers could be a reflection of the person’s own predisposition. But we also have experimental variation in whether a person’s friends were also treated by the experiment. We see that people are more likely to adopt cryptocurrency trading if their friends were also randomly treated by the campaign. We find no evidence of diffusion of cryptocurrency adoption in the control group. This is akin to a “first-stage” analysis that

1. We cannot merge people’s Venmo and PayPal accounts. In addition, the company did not conduct any large scale incentivized adoption experiments among Venmo users.

2. The incentive campaigns were emailed to people that were users of the PayPal platform and involved more than 30 million users on PayPal. The different incentives ranged from \$5 to \$35 and were provided to users if they opened a cryptocurrency account and traded on PayPal.

the campaign has the desired direct effect.

Online Gambling Experiment: The second source of variation comes from a set of quasi-natural experiments in the exposure to gambling, when thirteen U.S. states successively legalized online gambling and sports betting during our sample period. Before our sample period, online gambling was already legal in nine states. We again first use this variation to confirm that legalization has a direct effect on gambling and that peer networks matter for the adoption of online gambling. In a “first stage” analysis, we conduct an event study (i.e. a difference-in-differences analysis, including the use of methods from Callaway and Sant’Anna (2021)) to show that the legalization of online gambling within a state results in more gambling adoption and larger gambling volumes for people living in these states relative to states where gambling was never legalized.

This analysis confirms that there is a crowd out effect from gambling onto cryptocurrency trading. In order to identify the role of effects in gambling, we can take advantage of gambling shocks to a person’s peers. We are able to look at people who have friends living in a state where online gambling just became legal. This approach allows us to use the (exogenous) variation from the legalization of gambling in the state that a friend lives in, not the endogenous adoption decision of a friend. The latter variation might be prone to the typical reflection problem that people whose friends endogenously adopt an activity are themselves more prone to adopt it. We restrict our sample to people who live in states where gambling is already legal (to ensure that they can legally react to the peer adoption shock).³ We show that individuals who have a friend in a state where gambling just became legal are more likely to adopt gambling, than people in the same state who do not have such a network peer.

Equipped with these two experiments, we then study whether overlapping peer networks compete for a friend’s attention, time or resources. In particular, we analyze whether engagement by peers in one activity - gambling or cryptocurrency trading - negatively affects participation in the other. This analysis is feasible because, in our data, crypto and gambling peer networks only partially overlap. Specifically, in the PayPal sample, on average, only 9.2% of an individual’s crypto friends are also gamblers, and just 7.8% of their gambling friends are also PayPal Crypto users. Among all the friends, on average, there are 4% of an individual’s friends who are crypto users and 4.2% of an individual’s friends who are gamblers.

Our evidence confirms that people whose peers have an interest in one activity (partially) crowd out adoption and engagement of the alternative activity. Using first the crypto

3. We also repeat the analysis for all states, including those where gambling is not legal, and the results are qualitatively unchanged.

incentive experiment, we show that the treatment effect of the crypto incentive campaign is significantly attenuated for users with a higher number of gambling friends. Since this result relies on a heterogeneous treatment effect, the pre-existing peer network could reflect the higher propensity of a person to engage in one activity. However, we are able to isolate random shocks to a *peer's* exposure to crypto trading via the experiment and show that the peer effect on adoption is much smaller when the treated peer is a gambler. In other words, peers with a conflicting gambling interest do not transmit the positive exposure shock from the marketing experiment on to their friends. This effect is stronger in the treatment group and is of comparable magnitude to the direct peer treatment effect, but with the opposite (negative) sign.

We then examine the crowd-out effect from gambling onto crypto trading using the quasi-exogenous variation from gambling legalization: We find that individuals residing in states that legalize gambling reduce their cryptocurrency trading in response to gambling legalization. As discussed above, to identify the impact of peer effects on gambling adoption, we use the exogenous exposure to gambling in a person's peer network, through peers who live in states that make gambling legal. Specifically, we find that individuals significantly reduce their crypto trading volume when has a "gambling shock" by residing in a state that is exogenously treated with gambling legalization, compared to people who do not have peers living in exposed states. Moreover, this crowding-out effect from gambling to crypto is even more pronounced among users who have additional gambling-active peers.

We argue that these effects are driven by competition between peers for a friend's attention or resources in closely related activities not a general crowding out. Therefore, in a final step we study the extent to which peer effects in cryptocurrency and gambling spill over into other spending categories on PayPal or Venmo using retail transaction volume on the platforms. We find no evidence that peer-induced adoption of gambling or crypto trading crowds out other forms of spending on PayPal. However, overall spending on PayPal and Venmo goes up slightly since the crowd out between crypto trading and gambling is not one for one. This suggests that users may allocate a specific mental or attention budgets to risk-taking activities such as gambling or cryptocurrency trading, without allowing these behaviors to displace unrelated spending.⁴

Overall, these findings highlight a new channel - that peers with diverging interests compete for the attention and resources of individuals within their social networks. Thus peers engaged in competing activities can crowd out the adoption of new technologies or activi-

4. While we do not observe users' total consumption, we do capture a substantial share of their financial activity. In our sample, users who engage in gambling or cryptocurrency purchases via PayPal spend, on average, approximately 8.6% of their income through the platform.

ties. Our results also have important implications for empirical research: when researchers observe only a single outcome or dimension of peer influence, they may be capturing the net effect of multiple, potentially opposing and overlapping peer dynamics. The underlying peer effects may in fact be far more heterogeneous if offsetting behaviors within the network were observable.

1.1 Related Literature

There is a large literature on the role of social networks in economics. Reviewing this literature is beyond the scope of this paper, but a few excellent reviews can be found in (Jackson (2009)), (Jackson, Rogers, and Zenou (2017)) and (Bramoullé, Djebbari, and Fortin (2020)). As these reviews highlight, social networks play a significant role in a variety of settings and types of economic interactions, including finance, see (Kuchler and Stroebl (2021)). The literature has shown that not only do the number of immediate friends matter, but so do second order friends (e.g. Granovetter (1973) weak ties) and the particular structure of the networks, and where in the structure an individual sits. More closely related to our set up, there is a large literature studying how social networks affect the adoption of various types of technologies - a recent overview of the work on social networks and technology adoption in agriculture can be found in Suri and Udry (2022).

While a large part of the work on peer effects has used survey data from field surveys or experiments, which can be subject to recall bias, a few recent papers have looked at digital payment networks. Houeix (2024) studies the adoption of digital payments in Senegal using administrative data on all mobile money and digital payments accounts. The paper finds strong evidence that social networks matter for the adoption of digital payments, especially across sectors and space. Crouzet, Gupta, and Mezzanotti (2023) uses administrative data from one payment wallet in India to study the role of demonetization in the adoption of digital payments. The authors show that network externalities play an important role in explaining the diffusion of payment wallets. Our work adds to this literature by documenting for the first time a crowd out effects across competing activities within networks.

Our work is also related to a growing literature that suggests that trading and gambling might draw on the same underlying demand. Using variation from lottery-jackpots Gao and Lin (2015, RFS) and Dorn, Dorn, and Sengmueller (2015, Management Science) document across several different countries that trading volume by individual investors drops significantly in weeks when national lottery jackpots are large. Similarly, Cookson (2018, JFE) uses casino openings to show that access to casino gambling crowds out gambling-motivated demand for lottery-like financial assets. We add to this literature not only by showing the close substitution between gambling and crypto assets but more importantly we document

how pre-existing peer networks either amplify or impede the adoption of gambling or crypto trading.

Finally, we build on a few recent papers that have documented a crowd out effect of gambling on crypto trading using the staggered state-level legalization of sports betting after the 2018 Murphy v. NCAA decision as a large shock to the availability of a competing gambling technology. Baker, Balthrop, Johnson, Kotter, and Pisciotta (forthcoming/2025, JFE) find that legalization reduces net brokerage deposits by roughly 14–20%, with effects concentrated among frequent bettors and financially constrained households, who also increase credit-card debt and overdrafts. Hollenbeck, Larsen, and Proserpio (2024) use credit-bureau data to show that online sports-betting access lowers credit scores and raises bankruptcy rates within four years, concentrated among young men in low-income counties. Finally, Douidar, Henriksson, Pantzalis, and Park (2024, SSRN, "The Only Bet in Town?") show that sports-betting legalization reduces gambling-motivated local equity bias as further evidence of substitution between betting markets and lottery-like stock demand.

2 Relevant Context on Crypto Trading and Gambling

We first describe the relevant context and legal changes that allowed customers to access crypto trading as well as online gambling and sports betting on PayPal and Venmo during our sample period.

Cryptocurrency Trading on PayPal: In October 2020, PayPal enabled its users to trade and invest in cryptocurrencies directly on its platform. The supported tokens included Bitcoin, Ethereum, Litecoin, and Bitcoin Cash. Our data spans the period from the beginning of 2020 until the end of our sample period March 2023, Bitcoin accounted for 50.54 percent of the transactions, Ethereum 33.75 percent, Litecoin 9.74 percent, and Bitcoin Cash 5.97 percent. Users on PayPal did not directly hold the crypto assets; instead, the tokens were held in a custodian wallet and PayPal executed trades on behalf of users. By the end of April 2021, several external cryptocurrency trading platforms introduced new functionalities that allowed users to link their crypto accounts to PayPal, enabling PayPal also to serve as a payment method for transferring funds to these platforms. In our dataset, these external crypto platforms—hereafter referred to as Other Crypto Platforms (OCPs)—appear as merchants on the PayPal network. During our sample period, we observe \$1.56 billion in direct crypto transactions on PayPal, and an additional \$1.16 billion in transactions routed to OCPs.

Gambling Deregulation: Over the past decade, the regulatory landscape surrounding online gambling in the United States has undergone significant changes. Gambling regulation

is determined at the state level, and individuals must be physically present in a state where gambling is legal in order to place bets legally. Since 2010, the legalization of online gambling and sports betting has expanded considerably. Nevada was the first state to legalize online sports betting in 2010, with other states gradually following suit. As of 2025, online gambling is legal in twenty-two states, thirteen of which changed their regulations during our sample period. Prior to the beginning of our sample period in January 2020, online gambling was already legal in Nevada, Delaware, New Jersey, West Virginia, Pennsylvania, Iowa, Rhode Island, Indiana and New Hampshire. During the sample period, which runs from January 2020 to March 2023, online gambling was legalized in Colorado, Illinois, Tennessee, District of Columbia, Virginia, Michigan, Wyoming, Arizona, New York, Louisiana, Kansas, Maryland, Ohio and Massachusetts. However, Ohio and Massachusetts only enacted legalization in 2023. Table B2 reports the specific dates on which gambling became legal in each state. For the purposes of our analysis, we treat Colorado, Illinois, Tennessee, Virginia and Michigan as always legalized states since their legalization dates occurred before when Venmo was available as a channel for online gambling purchases.

The legalization of online gambling across states has several key features that are useful for our analysis. First, the staggered implementation of state-level regulatory changes creates a natural experiment that allows us to study diffusion in peer networks. Second, the contamination of the “control group” is minimal, as both online gambling sites and advertisement platforms adhere to state-level restrictions, limiting access and exposure for individuals residing in states where online gambling remains illegal.

Online gambling platforms restrict access to users in states where online gambling is illegal by monitoring and regulating IP addresses. Individuals are generally able to access these platforms and place bets only under two conditions: (1) they reside in a state where online gambling is legal, or (2) they reside in a gambling-illegal state but physically travel to a state where online gambling is permitted.⁵ In line with state-level regulations, major online advertisement platforms such as Google also abide by state laws and do not display gambling-related advertisements to users located in states where online gambling is prohibited.

3 Data Sources and Identification Strategy Overview

Our data comes from PayPal and Venmo, two of the largest digital payment systems in the United States, both owned by the same parent company. Compared to some of its competitors, such as Visa or Mastercard, PayPal and Venmo maintain detailed information on both

5. There remains a potential concern that some users may attempt to circumvent these restrictions through illicit means, such as using VPNs.

the merchant and customer sides of each transaction. As of 2023, PayPal had approximately 432 million active global accounts, while Venmo had approximately 110 million users over our sample period. In contrast, Zelle serves around 120 million consumer and small-business accounts, while Cash App has approximately 44 million active users. Our dataset consists of de-identified (encrypted) transaction-level data on PayPal and Venmo users, covering the period from January 1, 2020, to April 1, 2023.

For our analysis, we focus exclusively on U.S.-based users. We implemented a multi-stage filtering procedure to construct a clean and representative sample of individual-level payment activity. First, we exclude merchant accounts, commercial entities, and other non-personal accounts at the user level. Next, we remove closed accounts and users with unusually high numbers of connections who are likely to be merchants or small single person businesses - specifically, those with more than 200 unique payment partners. This process follows PayPal’s own screening method of “stealth” merchant accounts. At the transaction level, we filtered out unapproved payments. To address the issue of multiple-account ownership, we relied on PayPal’s “broad person entities” framework, which consolidates multiple accounts associated with the same individual, prioritizing those with demographic information and transaction activity. This comprehensive filtering approach ensures that our final dataset represents genuine person-to-person payment networks among individual US PayPal users with valid demographic information.

We apply an analogous filtering process to the Venmo data. As in the case of PayPal, we exclude commercial accounts, unapproved accounts, system accounts, and accounts with unusual activity patterns—specifically, those with more than 200 distinct payees or payers, or more than 50 instances of QR code money receiving during our sample period, who are likely to be small businesses or bots. To address the issue of users operating multiple Venmo accounts, we employ the same “broad person entity” framework used in the PayPal analysis, which consolidates accounts associated with the same underlying individual. In cases where multiple accounts map to a single entity, we retain the account with the most complete demographic information and the highest transaction activity.

We create two separate data sets to analyze the cryptocurrency trading experiment and the gambling legalization events. The PayPal dataset is used for the cryptocurrency experiment and Venmo data for the gambling legalization. This choice is driven by the following considerations. The randomized marketing experiments to promote cryptocurrency adoption provide us with exogenous variation to identify peer effects in crypto adoption. Unfortunately the firm only ran these on the PayPal platform but did not run these experiments on the Venmo network. In contrast, Venmo has a more comprehensive and denser peer-to-peer payment network, making it better suited for studying the diffusion of gambling behavior

through social networks following state-level legalization. Both platforms observe cryptocurrency and gambling transactions, and we leverage the strengths of each platform for the respective analyses.

3.1 Cryptocurrency Experimental Sample

For our analysis of the Cryptocurrency Experiment, we rely on a sample specifically selected by PayPal for a randomized marketing experiment designed to generate adoption. The resulting sample is described in Table 1A and includes 33.04 million users who had not adopted cryptocurrency prior to the campaign launch on February 15, 2022. Of these, 330,360 users (approximately 1%) were randomly assigned to the control group, while the remaining 33.22 million users served as the treatment group. To further refine our analysis, we constructed an attention metric based on users’ engagement with PayPal marketing emails unrelated to cryptocurrency. Specifically, we observed user interactions with promotional campaigns tied to partners such as Uber, Google Play, Spotify, and Instacart. We defined “attentive users” as those who opened at least one of these non-crypto promotional emails, providing us with a behavioral proxy for attentiveness and receptiveness to digital marketing.

3.2 Gambling Legalization Subsample

For the gambling natural experiment, we use Venmo data and construct a comprehensive sample of the Venmo user base. Even though we have data starting from the beginning of 2020, we chose August 1, 2021 as the starting point of our sample, when Venmo allowed its users to transfer money to gambling websites, which allows us to observe people’s gambling activities. We include only users who created their Venmo accounts before August 1, 2021, so that we can create their peer networks based on data prior to the start of gambling legalizations. Our final panel sample therefore spans 20 months, from August 2021 through March 2023, and including 90.97 million users across all U.S. states, which we refer to as the “full gambling sample.” Within this broader framework, we examine one more sub-samples: the Legalized Gambling Subsample, comprising 16.85 million users residing exclusively in states that experienced gambling legalization events during our study period (these states are detailed in the timeline in Appendix Table B2). Appendix Table B3 provides detailed description of all the samples used in our analysis.

Network Measures For each transaction, we have information about the date of the transfer, the transaction amount, the type of transaction, the merchant code if the transaction was with a merchant, and the unique user ID if the transaction was P2P. We use these data to construct parallel measures of social networks on each platform. In particular, we can

identify a person’s peers, which we call symmetric friends: these are users who have sent payments to and received payments from each other. We identify these friends using transactions during the pre-treatment period: January 1, 2020 to February 15, 2022 for the PayPal cryptocurrency experiment, and January 1, 2020 to July 31, 2021 for the Venmo gambling natural experiment. Importantly, we fix the peer network at the start of each experiment and do not update it during the treatment period. This ensures that our peer measures are predetermined relative to the treatment and cannot be affected by post-treatment changes in transaction behavior.

For our analysis, we use the number of symmetric payment friends that a given user has as a measure of the user’s overall peer network on the system, a variable we refer to throughout as *SymDegree*. The benefit of using *SymDegree* as our network connection measure is that (1) it ensures that the relationship between two users is mutual, and (2) it allows us to eliminate connections might have been hidden one-directional payments.

Building on this symmetric friend network structure, we further identify specific subsets of peers that engage in cryptocurrency and gambling activities. For the cryptocurrency experiment sample, we define crypto friends as symmetric payment friends who had purchased cryptocurrency before the campaign start date (February 15, 2022). This timing restriction enables us to isolate clean peer effects from friends’ prior behavior, as observed through our transaction-level data. For the gambling experiment sample on Venmo, we adopt a similar approach. We define gambling friends as symmetric payment friends—users with whom an individual has mutual Venmo transactions—who engaged in gambling activity but did not engage in any cryptocurrency activity prior to the baseline period (i.e., based on transactions before August 1, 2021). We impose this mutual exclusivity to isolate the distinct effects of each peer type; friends who engage in both activities would confound our ability to separately identify the influence of gambling-oriented versus crypto-oriented peers.⁶ Analogously, we define crypto friends as symmetric payment friends who engaged in cryptocurrency activity but did not engage in any gambling activity prior to the baseline period. Venmo’s more established and denser peer-to-peer network allows us to construct well-populated friend networks using this pre-period definition, yielding a clean identification strategy analogous to that used in the cryptocurrency experiment. Throughout, we refer to the number of crypto and gambling friends as *SymCrypto* and *SymGamble*, respectively.

We also analyze the overlap between users’ crypto and gambling symmetric friend networks. Among users with at least one symmetric friend, the average fraction of crypto friends is 1.7%, while the fraction of gambling friends is 2.66%. The overlap between the

6. We confirm that our results are qualitatively similar when we relax this restriction and allow for overlapping peer categories.

two behaviors is small: on average, only 0.13% of a user’s friends engage in both crypto and gambling activities. In the Venmo sample, When we condition on each peer group, we find that 9.76% of crypto friends also gamble, whereas 4.9% of gambling friends also engage in crypto trading. These results suggest that while the overall overlap is limited, the two peer networks are sufficiently distinct to allow us to study competing peer effects. These figures are broadly similar to the PayPal sample (9.2% and 7.8%, respectively), suggesting comparable network overlap structures across platforms despite differences in user bases.

User Characteristics In addition, for each user, we observe some of their demographic characteristics. PayPal constructs its demographic data using multiple resources in a prioritized order: (1) primarily, they rely on something called the PayPal DOB Compliance, a mandatory survey users complete to send, receive or withdraw funds over the PayPal system; (2) if unavailable, they turn to an external database provided by Acxiom; (3) finally, if needed, they use external estimates from Acxiom data. In particular, we observe a user’s age, a measure of their income, their state of residence, how actively they engage on the platform, and their digital transaction attributes (such as gamer, traveler, fashion shopper etc.). In our data, PayPal categorizes users into three age groups (18-29, 30-49, 50+), three income groups (<\$50K, \$50K-125K, >\$125K), and several engagement groups based on their activities on PayPal over the past year (low/mid/high engaged, likely to churn, churned, newly active, etc.). Table 1A shows summary statistics for these user characteristics for the PayPal user base (the first two columns) and compares them to summary statistics from the US census (the last two columns). As is clear, the PayPal user base, as a whole, looks quite similar to the US census on age and state representation of the larger states. In terms of income, the fraction of low-income individuals also looks similar, though the PayPal user base is less likely to be high-income compared to the census (note here that the income categories collected by PayPal and the census are different so we cannot do a clear direct comparison for income categories above low).

Table 1B shows the transaction and network summary statistics for the full PayPal user base in the topmost panel. On average, PayPal users have a small number of symmetric friends, only 0.118. This is not surprising, given that in our context, friends are the subset of people on the platform that a user conducts P2P transactions with back and forth. Users perform, on average, 20.5 transactions a year, though the 90th percentile of this variable is closer to 210. Of these transactions, on average, 2.54 are P2P and 16.8 are retail transactions per year. The fraction of the PayPal user base that has ever gambled is 1% and the fraction that has ever used other (identifiable) cryptocurrency platforms is 0.8%.

In Table 2, we show summary statistics for crypto users, cryptocurrency users, and gamblers, based on the universe of PayPal users and whether they had used each of these

technologies before February 15, 2022 (the date the first marketing incentives were implemented), respectively. There is, of course, overlap in these categories. There are about 44,000 users who were both gamblers and PayPal crypto users; 79,000 who were both PayPal crypto users and used other crypto platforms; 40,000 who were both gamblers and used other crypto platforms. Interestingly, we see that crypto users have more crypto friends than those using other crypto platforms, but have fewer friends than users who engage in gambling. The crypto users make fewer transactions per year (and a lower volume of transactions) than users who are on other crypto platforms and gamblers (who make the most transactions amongst these groups). Looking at the number of P2P transactions, crypto users and gamblers look quite similar. In terms of P2P volume, crypto users are the highest, followed by gamblers. In terms of retail transactions, similar patterns hold. The age breakdown of users is quite similar across these categories, but in terms of income, gamblers are much more likely to be high-income than cryptocurrency users.

Finally, we are able to identify and classify 4.1 million merchant accounts from the transaction data in PayPal; their business name, their state of operation, their business type and size ⁷ This data all comes from the underlying user transaction data so we do not have a lot of data on the merchants themselves. We use the data on their business type to track transactions from users into merchant accounts that are associated with cryptocurrency services as well as gambling services. Only 12.7% of users who send money to cryptocurrency exchanges outside of PayPal also directly buy crypto from PayPal. For gambling, we define gambling-related merchants as those who have government-licensed casinos for online or internet gambling. We can see this in the data as both Venmo and PayPal codes the types of merchants in their data. We can then trace Venmo and PayPal user transactions to this merchant.

On Venmo, we identify gambling activities by detecting payments sent to merchant accounts classified by Venmo as licensed online casinos, based on their internal merchant classification system. Crypto trading activity is directly observed through Venmo’s in-app cryptocurrency functionality, which allows users to buy and sell digital assets such as Bitcoin and Ethereum.

4 Empirical Framework

As mentioned above, our empirical analysis uses two main sources of identifying variation. The first is a set of marketing experiments that PayPal ran on their network. The second is quasi-experimental variation from the legalization of gambling across a number of US states,

7. This is a variable created by PayPal.

which we study using Venmo data.

4.1 Marketing Incentive Experiments in Crypto

After enabling cryptocurrency trading, PayPal launched multiple randomized A/B marketing experiments aimed at promoting user adoption of crypto trading. We exploit the exogenous variation introduced by these experiments to identify the impact of peer effects on adoption. Because these experiments were limited to a specific subset of users, our analysis is confined to those included in the experimental design - either as treated individuals or control participants.

We focus primarily on the first set of marketing campaigns conducted in the first quarter of 2022, which ran from February 15 to April 12. This campaign targeted 33.56 million users on the PayPal platform, with 335,004 randomly assigned to the control group and the remainder to the treatment group. Treated users were offered a \$5 crypto reward upon setting up a PayPal crypto wallet and making a purchase. A second campaign was conducted in the second quarter of 2022, running from April 22 to June 23. This campaign included approximately 12 million users in the treatment group and 596,551 in the control group. The incentive was significantly larger: users received a \$25 crypto reward for completing a single purchase of at least \$100 in cryptocurrency. Although the second campaign used significantly higher incentives, it involved fewer users and occurred later when crypto usage was already more established. For this reason, we do not focus on this experiment in the main analysis, but we report supporting results in the Appendix. As the campaigns did not have explicitly defined termination dates, we consider an experiment to have ended when a subsequent crypto-related campaign was launched to avoid contamination from overlapping treatments.

In Table 1B (the second panel), we compare how the main experimental sample we use compares to the overall user base of PayPal. Users in the experimental sample (treatment and control groups) have slightly more friends, and conduct more total transactions as well as P2P transactions (almost double) compared to the average PayPal user. However, they are not different based on their gambling or crypto adoption. In Appendix Tables A1 and A2 we show randomization balance holds well based on data from before the experiment for first and second experiments, respectively.

In Table 1B (the third panel), we compare the experimental sample to the sample that has symmetric friends. Conditional on having symmetric friends, individuals in the experimental sample unsurprisingly have an order of magnitude more symmetric friends, but they also conduct about double the number of transactions per year, about four times as many P2P transactions per year, and just under double the number of retail transactions. The users

with symmetric friends are, along all dimensions, much more engaged on the PayPal platform.

Using the first experiment, we run two sets of analyses. To test if the marketing incentive campaign had an overall effect on the adoption of crypto trading we use the following specification ⁸:

$$\begin{aligned} AdoptedCrypto_i = \alpha + \beta Treated_i + \gamma_1 SymDegree_i + \gamma_2 SymCrypto_i \\ + \psi Transactions_i + \delta X_i + \epsilon_i \end{aligned} \quad (1)$$

where *Adopted Crypto* is an indicator variable for whether the user adopts crypto on PayPal within the first two months after the start of the experiment; *Treated* is an indicator variable for whether the user received the crypto incentive treatment in the first campaign; *Sym Degree* is the size of the user's payments network; *Sym Crypto* is the number of the users' such friends who were already crypto users prior to the start of the experiment. In the X_i we control for the total number of PayPal transactions for the one year prior to the start of the experiment. In addition, all our specifications control for age, income and state of residence throughout. Note that our main coefficient of interest is β , the effect of the marketing incentive on the use of crypto.

Second, to study the impact of peer effects on crypto adoption, we use the experimental variation from the marketing incentive experiment in the following regression specification ⁹:

$$\begin{aligned} AdoptedCrypto_i = \alpha + \beta SymTreated_i + \gamma_1 SymDegree_i + \gamma_2 SymCrypto_i \\ + \psi Transactions_i + \delta X_i + \epsilon_i \end{aligned} \quad (2)$$

where, in addition to the variables defined in equation (1), *Sym Treated* is defined as the number of the users' payment friends who (randomly) were treated by the crypto incentive experiment. We estimate this specification separately for the treatment and control groups in the experimental sample. This allows us to see if there are reinforcement effects of the treatment in that sample, and whether there is diffusion to the control group. In these specifications, the variation comes from the number of treated friends being randomly treated controlling for the total number of friends a user has (i.e. the variable *Sym Degree*).

8. The coefficient on *Treated* is the same when we use no controls at all.

9. The coefficient on *SymTreated* is the same when we use no controls at all.

4.2 Natural Experiment: Legalization of Gambling

For the gambling analysis, we use a natural experiment where a set of US states (described above) legalized online gambling over our sample period. This sample includes a total of 90.97 million PayPal users.

In Table 1A, we show summary statistics for this gambling sample. In the table, we compare the demographic characteristics of Venmo users (overall sample and campaign participants) with U.S. Census data, showing high similarities in age, income, and geographic distribution. Both the overall PayPal sample and U.S. Census data are dominated by individuals aged 30–49, with similar shares of younger (18–29) and older (50+) individuals, though the campaign sample skews younger (31.67%) with fewer older users (25.43%). Income distributions align closely after adjusting for category definitions, with middle-income individuals comprising the largest group in both datasets, followed by lower- and higher-income groups. Geographic representation is consistent, with California, Texas, and Florida leading across all samples. Overall, the PayPal user base closely mirrors the U.S. population, with the campaign sample differing slightly due to its younger demographic.

We first use a standard event study or generalized difference-in-differences (DiD) framework to document the impact of gambling regulation changes. Our control group consists of states where online gambling was already legal before our baseline period of August 1, 2021 (we also repeat the analysis using only states where gambling was never legalized). The treatment group comprises states that legalized online gambling after this date, with the timing of treatment determined by each state’s specific legalization date.

The regression specification we use is a standard two way fixed effects model, implemented as follows:

$$Y_{it} = \beta Legalized_{it} + \mu_i + \gamma_t + \epsilon_{it} \quad (3)$$

where Y_{it} is the relevant outcome (we describe the outcomes we look at next); $Legalized_{it}$ is an indicator variable for whether user i ’s residential state has legalized online gambling by month t ; the μ_i are a set of user fixed effects; the γ_t are a set of year fixed effects. In terms of outcomes, we use the dollar amount of online gambling spending of a given user in a given month (what we call *Gamble Vol*); the share of online gambling spending in the total transaction volume (what we call *Gamble Share*).

To analyze exogenous peer shocks to gambling adoption, we look at the impact that the legalization of gambling has on an individual’s friend. Instead of using the endogenous adoption by a friend, we identify shocks to the gambling access of an individual’s friend, if the friend lives in a state that makes gambling legal. For this analysis we construct a

sample of individuals living in states where gambling was legal prior to August 1, 2021, but who had not engaged in gambling until the legalization of online gambling in Wyoming on September 1, 2021 (the first legalization in our sample period after Venmo enabled their crypto platform). The rationale is to focus on people who legally can react to shocks from their friends. This sample includes 74 million Venmo users. For this sample, we run the following specification:

$$Y_{it} = \beta SymLegalized_{it} + \mu_i + \gamma_t + \epsilon_{it} \quad (4)$$

where *Sym Legalized*, our primary explanatory variable, is a dummy for whether any of a user’s symmetric payment friends lives in a state where online gambling has been legalized. For this specification, we report results only for *Gamble Vol* and *Gamble Share*). The control group are people in the same states who do not have gambling exposure through a friend’s state legalization. We include all friends in states where gambling is newly legalized, independent of whether the friend adopted gambling or not. This is akin to an intent to treat analysis.

Callaway and Sant’Anna Method: To analyze the robustness of our estimated effects of online gambling legalization, we also employ the Callaway and Sant’Anna (2021) difference-in-differences estimator, which offers several advantages over traditional two-way fixed effects (TWFE) specifications when treatment timing varies across units. This methodology explicitly accounts for heterogeneous treatment effects across both time and treatment cohorts. A key advantage of the approach is that it constructs clear comparisons between treated units and never-treated units, rather than potentially using already-treated units as controls. Additionally, the estimator provides transparent aggregation of group-time average treatment effects into interpretable parameters of interest, where we choose event-study coefficients in our analysis. Our implementation follows the recommendations in Roth (2024) to ensure robust estimation and valid inference. Specifically, we set the base period to universal, using the same pre-treatment period as reference for all comparisons to ensure symmetric construction of pre-treatment and post-treatment coefficients. We examine an event window of 12 months before and after treatment, use never-treated units as the control group, and employ the doubly robust estimation method to provide protection against model misspecification. Standard errors are clustered at the state level to account for within-state correlation of outcomes.

5 Results

In a first step we now confirm that both experiments, the crypto incentive campaign and the online gambling legalization, had the expected direct effects: Users who have friends that are also exposed to the same activity see greater adoption of this activity, i. e. there is a positive amplification effect if a person has peers engage in the same activities.

5.1 Adoption of Crypto Trading

In Table 3, we first confirm that the incentive campaign had an impact on the adoption of cryptocurrency trading on the PayPal platform, using the regression specification in equation (1) above. Columns (1), (2) and (3) show results for the full experimental sample; Columns (4) through (6) condition on the sub-sample of attentive users, i.e. those who have a history of responding to email campaigns. The outcome variables here is *AdoptedCrypto*, which is a binary indicator variable equal to 1 if the user purchased cryptocurrency on PayPal within two months of the experiment’s start date (February 15, 2022), and 0 otherwise.

The table shows that the incentive experiments had a significant impact on the adoption of cryptocurrency, when compared to the mean in the control group (which is reported at the bottom of the table). From Column (1), we see that the incentives increase the adoption of crypto in the two months following the experiment by almost 150%. Adding controls in Columns (2) and (3), does not change the results.

This effect of the treatment also holds in the sample of attentive users: The adoption of crypto trading in this sample is high overall and the effect of the treatment is also slightly larger - in this sample the incentives increase the probability of a user purchasing crypto by almost 220%. Appendix Table 3 shows a similar set of results for the second experiment.

5.1.1 Amplification through Treated Peers

In Table 4, we now document the role of peers in crypto adoption using the specification in equation (2) above. The dependent variable again is *AdoptedCrypto*. We run these specifications separately for the treatment and control groups, to allow for differential diffusion across the two groups. The odd columns show the results for the treatment group; and the even columns for the control group. As we can see, in Column (1), treated friends amplify the adoption for the treated users, which suggests that there is an amplifying effect from friends being treated. However, there is no evidence of a similar amplification effect in the control group, see Column (2). This is similar to the findings in Duflo et al. (2023). Looking at magnitudes, an additional treated (payment) friend leads to an increase in the probability of adopting crypto by 0.04 percentage points. Given the diffusion rate of crypto in

the sample is only 0.07%, this is about a 150% increase in the probability of adoption from the treatment. Adding controls for *SymCrypto* in columns (3) and (4) does not change the results.

In Columns (5) and (6), we separate out the number of treated friends into whether there is only one treated friend or more than one. Again, we see diffusion and amplification effects in the treatment group. However, in the control, we do not see large effects with just one treated friend, but we do see large (in magnitude, though not statistically significant, likely due to the small size of the control group) effects of having more than one treated friend in the control group. It seems that perhaps more treated friends are needed for there to be any diffusion to the control group. In terms of magnitudes, having more than one treated friend raises the probability of adoption crypto by 30%.

In columns (7) through (10), we show the effects of the incentive campaign for the sample of attentive users. This sample is about 10% the size of the overall sample in the incentive experiment. We see similar effects, if not slightly larger effects in this sample, both for the treatment and control groups. However, when we split out the number of treatment friends to look separately at users with one friend vs. users with more than one friend (columns (9) and (10)), we do see some differences. We find effects mostly for those with a single friend. The effects are large, negative but not statistically significant for users with more than one friend (though we should note that among the sample of attentive users, very few have more than one friend, approximately only 1% relative to about 5% in the overall experimental sample so it is unsurprising that this coefficient is noisily estimated).

Appendix Tables A4 and A5 show the heterogeneity in peer effects, by the characteristics of the peers. In Appendix Table A4, we examine how individuals of different age groups are influenced by the treatment status of their friends from different age groups. Columns (1) and (2) respectively show the treatment and control groups of the full experimental sample; Columns (3) and (4) condition on high-age users (50+); Columns (5) and (6) condition on middle-age users (30-49); and Columns (7) and (8) condition on low-age users (18-29). In Appendix Table A5, we examine how individuals of different income groups are influenced by the treatment of their friends from different income groups. Columns (1) and (2) respectively examine the treatment and control groups of the full experimental sample; Columns (3) and (4) condition on high-income users (>\$125K); Columns (5) and (6) condition on medium-income users (\$50-125K); and Columns (7) and (8) condition on low-income users (<\$50K). While we find evidence of peer effects across age and income groups, the results exhibit some variation. The treatment effect is generally stronger among younger and lower-income users, potentially indicating a greater openness to crypto adoption in these demographics. However, some estimates, particularly for high-income and older users, are noisier, suggesting

that peer influence may be less consistent or that additional factors (such as prior financial experience or risk tolerance) moderate these effects.

5.2 Adoption of Online Gambling

In Table 5, we analyze the natural experiment of gambling legalization on the adoption of gambling using Venmo data. We use the DiD framework described above (see equation (4)) to look at the impact of the legalization of online gambling in an individuals’ state on their online gambling spending. For this table, we utilize two primary dependent variables to measure user engagement with gambling: (1) $GambleVol_{i,t}$, which captures the total dollar value that user i transfers to online gambling merchants in a given month t ; and (2) $GambleShare_{i,t}$, which represents the proportion of user i ’s online gambling spending relative to their total expenditures across all goods and services including cryptocurrency purchases in a given month t . Columns (1) and (2) examine the user’s online gambling volumes for the full sample as defined above; Columns (3) and (4) restrict the sample to states that experienced a gambling legalization shocks.

Overall, we find large effects of the legalization of online gambling in a state. For any given Venmo user (in the full sample, see Column (1)), the legalization of online gambling raises gambling volumes by \$1.31, which is about a 375% increase in gambling expenditures (the mean is low because a large share of Venmo users do not gamble). Column (2) shows that the effects on the share of total transactions attributed to gambling increased by 0.52 percent points, which, while seemingly small, represents a meaningful shift in consumer spending patterns. The effects are similar when we analyze only the sample of users in states that legalized gambling during the period (Columns (5) and (6)), where the estimated effect is \$1.27.

This table serves as an important foundation for the subsequent analysis of network effects. By first establishing that gambling legalization had a direct effect on gambling behavior, we can next examine how this shock diffuses through social networks.

To validate our TWFE estimates and address potential concerns about heterogeneous treatment effects across cohorts, in Figure 1, we also implement the Callaway and Sant’Anna (2021) difference-in-differences estimator. This methodology explicitly accounts for heterogeneous treatment effects across both time and treatment cohorts, avoiding the potential “negative weighting” problems that can arise in standard TWFE models. Figure 1 displays the dynamic effects of online gambling legalization on online gambling consumption. The pre-treatment coefficients are consistently close to zero, providing strong support for the parallel trends assumption. Upon legalization (event time 0), we observe an immediate and substantial increase in online gambling consumption. The aggregated treatment effect is 0.99

(SE = 0.055), which is consistent with our TWFE estimate in Table 6. This effect remains positive and statistically significant throughout the post-treatment period, and the narrow confidence intervals suggest precise estimation.

5.2.1 Peer Effects and the Legalization of Gambling

In Table 6 we now look at the role of peer effects on gambling by analyzing the impact on a person’s gambling activities if they have a friend who lives in a state where gambling becomes legalized (as per equation (5)). We focus on monthly gambling volume as the outcome variable. Since the legalization of gambling in a state is not in the control of the friend, the legalization creates exogenous variation in the friend’s exposure to gambling. This allows us to study whether the random shock to the friend’s exposure to gambling is transmitted to their peer. In this specification, we hold the peer network fixed and look at shocks to the peer’s interests. This approach provides much better identified peer effects, than relying, for example, on an analysis of heterogeneous treatment effects using the size or gambling interests of a person’s peer network, since the composition of network links is endogenous and could reflect the person’s own propensity to gamble. For this analysis we include the sample of people who live in states where there was no change to gambling legalization, but who did not gamble themselves.

Column (1) of Table 6 shows that there is a strong positive effect on a person, when a friend in another state is exposed to gambling being legalized. The coefficient on *SymLegalized* is \$1.46 and highly significant. In Column (2), we also look at the heterogeneous treatment effects by whether the user had other friends who are gamblers. The estimated treatment effect is significantly amplified if the user has other gambling friends: each additional gambling friend increases the peer legalization effect by \$1.26. Columns (3) and (4) further show that having crypto friends also amplifies the peer effect on gambling, with each additional crypto friend increasing the effect by \$1.87.

Figure 2 again replicates the main analysis using the Callaway and Sant’Anna estimator for peer effects on gambling consumption. Panel A presents event-study estimates using the subsample of all users, showing an aggregated coefficient of 2.28 (SE = 0.29). Panel B reports estimates for users with at least one gambling peer, with an aggregated coefficient of 2.11 (SE = 0.196). The pre-treatment coefficients are close to zero in both panels, supporting the parallel trends assumption. The coefficients are similar across both samples, confirming that peer legalization effects on gambling consumption are robust and statistically significant regardless of the sample considered.

6 Competing for Peer Attention

Equipped with the experiments described in the previous section, we can now analyze whether competing interests of peers within a network crowd out the adoption of other activities by their friends. This is the most novel part of the analysis, since we are uniquely able to observe multiple activities of peers on the PayPal and Venmo networks. In other words, we ask whether gambling friends amplify or detract from crypto adoption. And vice versa, are people who have more crypto friends see less adoption of gambling?

6.1 Peer Competition and Crypto Adoption

We first analyze if friends who have (competing) gambling interest affect the adoption of crypto trading on the PayPal platform. The regression specifications mimics those above but we now focus on whether the treated friend has been engaged in gambling, and thus might have a competing interest in a different activity. If our hypothesis of competing network effects is true, we would expect treated friends who are gamblers to have a negative impact on their friend’s adoption of crypto trading.

$$\begin{aligned} \text{AdoptedCrypto}_i = & \beta \text{SymTreated}_i + \eta \text{Gambled}_i + \sigma \text{SymGamble}_i \\ & + \rho \text{SymGambleTreated}_i + \delta X_i + \epsilon_i \end{aligned} \tag{5}$$

where *Gambled* is an indicator variable for whether the user was already a gambler prior to the experiment; *Sym Gamble* is defined as the number of the users’ payment friends who were already gamblers prior to the start of the experiment (as above); *Sym Gamble Treated* is defined as the number of the users’ friends who gambled and (randomly) received the crypto marketing incentive treatment described above. The latter group is unfortunately very small.

In Table 7, we show the results from this analysis. Columns (1) and (3) analyze the treatment group, while Columns (2) and (4) analyze the control group, using the full experimental sample. Columns (1) and (3) show that having a friend who is a gambler (*SymGamble*) reduces an individual’s probability of adopting PayPal Crypto by 0.034 percentage points. The magnitude of this effect is as large as the direct effect from the incentive campaign, but the sign goes in the opposite direction and therefore undoes the effect of the average peer being treated by the incentive campaign. The effect of *SymGambleTreated* on crypto adoption is also negative and the magnitude is larger for users in the treatment group. But the results are not statistically significant at conventional level, potentially highlighting the lack of power. In Columns (3) and (4) redo Columns (1) and (2) but decompose *SymTreated* to

two dummy variables like Table 4. The result remain similar.

Overall, these findings highlight that gambling and crypto adoption compete for peer attention— while being incentivized by the marketing experiment increases the likelihood of adoption, if a person has friends who are already gambling, their likelihood of adoption is significantly reduced.

6.2 Peer Competition and Gambling Activities

We now turn to the natural experiment of gambling legalization to study if heightened gambling exposure leads to a crowding out of cryptocurrency trading. We use the same difference in difference estimation as before, but look at the effect on cryptocurrency trading. Table 8, reports the results where the dependent variable is $CryptoVolume_{i,t}$, which measures the total dollar value that user i spends on cryptocurrency purchased through Venmo’s crypto platform in month t .

Columns (1) through (4) of Table 8 show results for the full sample of people affected by the gambling legalization, including the large fraction of people who do not trade cryptocurrencies. Columns (5) through (8) restrict the sample to those who were crypto traders prior to the legalization of online gambling. From Column (1), the direct effect of the legalization is strongly negative; crypto trading decreases by 0.02\$ after the legalization of gambling compared to non-legalizing states. In addition, we see that the negative effect on crypto trading is particularly strong for people who have symmetric gambling friends: in Column (2), each additional gambling friend decreases crypto volume by \$0.18. In Column (3) we repeat this analysis but separately break out people who have one gambling friend or more than one gambling friend. We confirm that the negative effect of gambling legalization on crypto trading increases significantly for people who have at least one gambling friend (\$0.22 reduction), and the effect doubles for people with more than one friend (\$0.44 reduction). In Columns (5) to (8), we repeat the same analysis but condition only on Venmo users who are crypto traders. Not surprisingly the estimated coefficients are now much larger, since we do not include the large fraction of people who never trade cryptocurrencies: the direct effect is \$2.39 (Column 5), and each additional gambling friend reduces crypto volume by \$3.42 (Column 6). Qualitatively, the results are very similar. Interestingly, Columns (4) and (8) show that having crypto friends attenuates this crowd-out effect: each additional crypto friend increases crypto volume by \$0.06 in the full sample and by \$7.87 among crypto traders, partially offsetting the negative pull from gambling peers.

Figure 3 again provides evidence of this crowd-out effect using the Callaway and Sant’Anna estimator. The figure shows the effects of gambling legalization on cryptocurrency purchases, with predominantly negative point estimates in the post-treatment period. The aggregated

coefficient is -4.5 (SE = 1.67). The pre-treatment coefficients show some volatility but remain statistically insignificant, supporting the parallel trends assumption. These results corroborate our TWFE findings in Table 10, confirming that gambling legalization reduces cryptocurrency trading activity.

Overall, these results suggest that increased access to gambling activities crowds out crypto trading on average. But this crowd out effect is significantly amplified for people who have at least one or several peers who are also gamblers. We interpret this as suggestive evidence that peers with gambling interests generate a “pull” effect, away from crypto activities. Conversely, crypto friends appear to generate a countervailing “pull” effect that partially anchors users to cryptocurrency trading, mitigating the crowd-out from gambling legalization. As discussed above, the reason these results are only suggestive is that people who have a larger density of gambling friends, might themselves have a latent predisposition to gambling and similarly for crypto trading.

To address this reflection problem, we employ our second identification strategy that relies on exogenous shocks to the gambling exposure of a person’s friends via the legalization of gambling in the state that a friend lives in, as discussed above.

$$CryptoVolume_{it} = \beta Legalized_{it} + \sigma_1 Legalized_{it} * SymGamble_i + \mu_i + \gamma_t + \epsilon_{it} \quad (6)$$

Table 9 uses $CryptoVolume_{i,t}$ as the dependent variable. In Column (1) the coefficient on $SymLegalized$ is negative and significant - gambling legalization in a friend’s state significantly reduces monthly crypto purchases. In Columns (2)–(4) we now interact the treatment effect, $SymLegalized$, with the number of a person’s peers that are gamblers. The negative and significant coefficient on $SymLegalizedXSymGamble$ in Column (2) (\$0.17) suggests that the negative effect from gambling legalization in one friend’s state is even amplified if the person has other friends who are gambling. In Columns (3) and (4) we also add an interaction term of $SymLegalizedXSymCrypto$, which shows that crypto friends attenuate this crowd-out effect: each additional crypto friend increases crypto volume by \$0.07 (Column 3) and \$0.13 (Column 4), again suggesting that crypto peers exert a countervailing pull that partially offsets the impact of a friend’s gambling shock.

Figure 4 again replicates the main specification using the Callaway and Sant’Anna estimator. Panel A presents event-study estimates for all users, showing an aggregated coefficient of -0.49 (SE = 0.17). Panel B reports estimates for users with gambling peers, with an aggregated coefficient of -0.37 (SE = 0.20). The point estimates remain consistently below zero throughout most of the post-treatment period, confirming that peer exposure to

gambling legalization reduces cryptocurrency purchasing activity. These results corroborate our TWFE findings and suggest that peer gambling legalization exerts downward pressure on cryptocurrency purchases, and the transmission mechanism through social networks is robust.

6.3 Peer Competition and Crowd Out of Other Transactions

Finally, we want to understand if the crowd-out effects from gambling legalization are contained to crypto trading or if we observe other activities being crowded out as well. In the Venmo data as we can observe also all the other expenditures a user makes on the platform on a monthly basis. While Venmo transaction on average constitute only about 10% of a user’s annual income, and thus not a person’s total consumption stream, the expenses are quite stable across months. In particular, we run the following specification:

$$\begin{aligned} RetailTransactionVol_{it} = & \beta Legalized_{it} + \sigma_1 Legalized_{it} * SymGamble_i \\ & + \sigma_2 Legalized_{it} * SymCrypto_i + \mu_i + \gamma_t + \epsilon_{it} \end{aligned} \quad (7)$$

where $RetailTransactionVol_{i,t}$ is the US dollar value of retail spending each month t on the Venmo platform for a given user i , but after taking out any gambling or crypto expenditures.

Table 10, Column (1) shows that there is no negative spillover from gambling legalization onto other retail spending of treated customers, if anything there is small increase in other spending. In Columns (2) through (4) we add the interaction terms of $LegalizedXSymCrypto$ and $LegalizedXSymGambling$. The coefficients on these interaction terms are negative but similar in magnitude to the main effect of legalization suggesting that even people with more gambling or crypto friends do not see a net crowd out of other spending.

Figure 5 provides confirmation of the TWFE results, using the Callaway and Sant’Anna estimator. The figure shows the effects of gambling legalization on retail transaction volume, measured as before. The pre-treatment coefficients are consistently close to zero, supporting the parallel trends assumption. Following legalization, we observe an immediate and sustained increase in total spending, with effects ranging from approximately 0.5 to 2.0 dollars throughout the post-treatment period. These results corroborate our TWFE findings in Table 12, confirming that gambling legalization does not crowd out other spending on Venmo.

The results suggest that users might set a specific attention or financial budget for similar activities so that one activity in this category crowds out another one, in our case online

gambling and cryptocurrency trading. But we do not see that this crowding out spills over to other spending categories. Of course, we cannot rule that some crowding out might happen on other spending that we do not observe.

7 Conclusion

Using transaction level data from the PayPal and Venmo platform which provides us with payment transactions of more than 70 million users, we document a new mechanism of crowd-out between different activities when a person’s peers have competing interests. A large literature has shown that peers can have a positive impact on the transmission of information or the adoption of new behaviors or technologies. Most of these papers study one activity at a time and look at the impact of peers that have aligned interests. In this paper, we are able to show that there can be impeding or crowding out effects on the adoption of particular activities, if some peers within a network have diverging interests, and compete for the attention or time of their network members. In our context, we show that peer exposure to gambling strongly reduces a friends engagement in crypto currency trading, and visa versa. We do not find significant crowd out of other spending on the payment platform, which suggests that users might set time or even financial budget for similar (risk-taking) activities. Therefore, substitution might be stronger between these similar activities but not the rest of a user’s spending. More research will be needed to determine how these competing peer effects affect a multitude of products or services. But our results provide a first example of the role of competing peer interests for user adoption.

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Table 1A: Demographic Summary Statistics, PayPal Users and US Adults from the Census (PayPal Sample)

This table presents the distribution of PayPal users and U.S. adults across age groups, income levels, and the six most populous states. The PayPal sample is categorized into three age groups (18–29, 30–49, and 50+) and three income brackets (<\$50K, \$50K–\$125K, and >\$125K). The table also reports demographic statistics from the U.S. Census for comparison. The six states with the largest representation in the sample—California, Texas, Florida, New York, Pennsylvania, and Illinois—are shown separately.

Overall Sample			In Campaign		US Census		
Age	Percentage	Count	Percentage	Count	Age	Percentage	Count
18-29	25.15%	32.93M	31.65%	10.46M	18-29	24.02%	53.26M
30-49	41.14%	53.86M	42.87%	14.16M	29-49	39.2%	86.91M
50+	33.71%	44.12M	25.48%	8.42M	50-69	36.77%	81.52M
Total						100%	221.70M
Income							
Low (<50k)	42.98%	56.27M	41.67%	13.78M	<50k	41.5%	49.45M
Medium (50k-125k)	44.51%	58.27M	45.13%	14.91M	50k-100k	36.92%	43.99M
High (125k +)	12.50%	16.37M	13.17%	4.35M	100k +	21.59%	25.72M
Total	100.00%	130.91M	100.00%	33.04M		100%	119.17M

Note: The income data from US Census is the Full-Time, Year-Round Workers with Earnings.

Table 1B: Summary Statistics, PayPal and Venmo User Transactions and Networks

This table displays the summary statistics for our main variables. We display user characteristics of the full sample and sub-samples of users involved in the 2021 Q1 experiment and the gamble natural experiment.

	Obs	Mean	P25	P50	P75	P95	P99
All PayPal Experiment Participants							
Symmetric Degree	33.04M	0.157	0	0	0	1	3
Number of Total Transactions Per Year	33.04M	30.9	3	11	37	123	241
Number of P2P Transactions Per Year	33.04M	4.6	0	0	3	23	62
Number of Retail Transactions Per Year	33.04M	24.5	1	7	28	104	211
Fraction of People Ever Gambled	33.04M	0.00985	0	0	0	0	0
Fraction of People Ever used Crypto	33.04M	0.00773	0	0	0	0	0
Venmo Gamble Legalization Sample							
Symmetric Degree	90.97M	3.61	0	1	5	16	28
Number of Total Transactions Per Year	90.97M	29.1	1	11	38	117	210
Number of Retail Transactions Per Year	90.97M	0.657	0	0	0	2	14
Symmetric Crypto	90.97M	0.0603	0	0	0	1	1
Symmetric Gamble	90.97M	0.121	0	0	0	1	2
Fraction of People Ever Gambled	90.97M	0.0125	0	0	0	0	1
Fraction of People Ever used Crypto	90.97M	0.00984	0	0	0	0	0

Note: In the top panel we show summary statistics for the sub-sample of users involved in the PayPal experiment.

In the second panel, we show summary statistics for the gamble natural experiment sample in Venmo.

Table 2. Gamblers and PayPal Crypto Users (PayPal Sample)

This table reports summary statistics for two distinct user groups: PayPal crypto users and gamblers. Gamblers are defined as individuals who have engaged in gambling or betting transactions via PayPal with online gambling merchants during the sample period. PayPal crypto users are those who have purchased cryptocurrency directly through PayPal. The table presents key transaction and demographic characteristics, including network connectivity (symmetric degree), transaction activity (total transactions, P2P transactions, and retail transactions per year), and income and age distribution. The second column of each group reports standard deviations for each variable.

	Crypto N=1.17M		Gamble N=840K	
	Crypto Mean	Crypto SD	Gamble Mean	Gamble SD
Symmetric Degree	0.3339	0.8986	0.4285	1.0847
Number of Total Transactions Per Year	57.9902	91.3402	77.2124	90.8758
Total Transaction Volume Per Year	3,756.87	6,993.94	5,931.34	19,988.76
Number of P2P Transactions Per Year	10.6413	25.8502	9.0638	24.3347
P2P Transaction Volume Per Year	1,421.96	4,279.74	1,588.00	8,202.94
Number of Retail Transactions Per Year	42.5620	77.0871	61.5382	77.9577
Retail Transaction Volume Per Year	1,931.31	3,696.03	3,216.34	7,053.03
Age: 50+	0.2400	0.4271	0.1891	0.3916
Age: 30-49	0.5264	0.4993	0.5345	0.4988
Age: 18-29	0.2336	0.4231	0.2763	0.4472
Income: >\$125K	0.1176	0.3221	0.2082	0.4060
Income: \$50-125K	0.4321	0.4954	0.4911	0.4999
Income: <\$50K	0.4503	0.4975	0.3007	0.4586

Note: These are subsets of the full PayPal user base, based on whether they use a given financial technology.

There is overlap in users across these categories.

There are about 43k users who were both gamblers and PayPal crypto users.

T-tests of differences in means between crypto and gambling users reject the null of no differences for all characteristics.

Table 3. Adoption of Crypto in Incentive Experiment (PayPal Sample)

This table presents regression estimates examining the effect of the 2021 Q1 crypto incentive experiment on the likelihood of adopting cryptocurrency on PayPal. The dependent variable, *Adopted Crypto*, is a binary indicator equal to 1 if a user adopts crypto within the first two months after the experiment start and 0 otherwise. Columns (1)–(3) report results for the full experimental sample. Columns (4)–(6) restrict the analysis to the sub-sample of attentive users, defined as those who opened the email PayPal sent them regarding the marketing incentive campaign. The key independent variable, *Treated*, indicates whether a user was assigned to receive the crypto incentive. *Sym Crypto* measures the number of symmetric (mutual) connections who are crypto users before the experiment. *Sym Crypto* = 1 and *Sym Crypto* > 1 differentiate between having exactly one and more than one crypto-using friend. Additional covariates include *Sym Degree*, capturing overall network connectivity, and *Log Num Txn*, the logarithm of the number of total transactions in the past year. All regressions control for age, income, and state fixed effects where indicated.

	Full Experiment Sample			Attentive Users		
	(1)	(2)	(3)	(4)	(5)	(6)
Treated	0.4466*** (0.047)	0.4474*** (0.047)	0.4474*** (0.047)	0.8691*** (0.205)	0.8683*** (0.204)	0.8678*** (0.204)
Sym Crypto		1.3599*** (0.067)			2.4406*** (0.298)	
Sym Crypto = 1			1.311*** (0.070)			1.9667*** (0.316)
Sym Crypto >1			4.1779*** (0.415)			13.8774*** (1.776)
Sym Degree		0.1765*** (0.009)	0.1755*** (0.009)		0.1962*** (0.039)	0.1898*** (0.039)
Log Num Txn		0.1838*** (0.003)	0.1839*** (0.003)		0.2355*** (0.016)	0.2362*** (0.016)
Intercept	0.2755*** (0.047)	-0.1027 (0.122)	-0.1027 (0.122)	0.4446* (0.203)	0.9202 (0.583)	0.9223 (0.583)
Control Mean	0.0003	0.0003	0.0003	0.0004	0.0004	0.0004
Age	N	Y	Y	N	Y	Y
Income	N	Y	Y	N	Y	Y
State	N	Y	Y	N	Y	Y
R-Squared	0.00	0.0003	0.0003	0.00	0.0006	0.0006
Adj. R-Squared	0.00	0.0003	0.0003	0.00	0.0006	0.0006
Observations	33.04M	33.04M	33.04M	3.11M	3.11M	3.11M

Note: Standard errors are reported in parentheses.

Coefficients and standard errors are multiplied by 1,000 for readability.

Statistical significance at the ten, five, and one percent levels is denoted by *, **, and ***, respectively.

Please refer to Appendix Table B1 for variable definitions.

Table 4. Peer Diffusion of Crypto in Treatment and Control Groups of Incentive Experiment (PayPal Sample)

This table examines the peer effects of the 2021 Q1 crypto incentive experiment by analyzing whether treated users are more likely to adopt crypto when their friends are also treated. The dependent variable, *Adopted Crypto*, is a binary indicator equal to 1 if a user adopts cryptocurrency on PayPal within the first two months after the experiment start and 0 otherwise. Columns (1), (3), (5), (7), and (9) report results for the treatment group, while Columns (2), (4), (6), (8), and (10) analyze the control group. The key independent variable, *Sym Treated*, captures whether a user's symmetric (mutual) connections were assigned to the crypto incentive treatment. *Sym Treated* = 1 and *Sym Treated* > 1 further distinguish between having exactly one and more than one treated friend. Additional covariates include *Sym Crypto*, which measures the number of symmetric connections who are crypto users before the experiment, *Sym Degree*, which represents overall network connectivity, and *Log Num Txn*, the logarithm of the number of total transactions in the past year. All regressions control for age, income, and state fixed effects where indicated.

	Full Experiment Sample						Attentive Users			
	Treatment (1)	Control (2)	Treatment (3)	Control (4)	Treatment (5)	Control (6)	Treatment (7)	Control (8)	Treatment (9)	Control (10)
Sym Treated >0	0.4191*** (0.027)	0.0621 (0.165)	0.3592*** (0.027)	0.0415 (0.168)			0.4644*** (0.124)	0.0955 (0.707)		
Sym Treated = 0					0.3595*** (0.027)	0.0413 (0.168)			0.4701*** (0.124)	0.1004 (0.707)
Sym Treated >1					0.1717** (0.062)	0.5442 (0.379)			-0.4933 (0.285)	-0.5212 (1.637)
Sym Crypto			1.483*** (0.068)	0.6383 (0.414)	1.4615*** (0.068)	0.6990 (0.416)	2.6239*** (0.303)	-0.5423 (1.747)	2.5178*** (0.305)	-0.5910 (1.751)
Sym Degree	0.2415*** (0.011)	0.1344 (0.069)	0.0741*** (0.012)	0.0721 (0.072)	0.0956*** (0.013)	0.0135 (0.083)	0.0672 (0.053)	-0.0463 (0.291)	0.1713** (0.060)	0.0206 (0.333)
Log Num Txn			0.1822*** (0.003)	0.0728*** (0.021)	0.1820*** (0.003)	0.0735*** (0.021)	0.2340*** (0.016)	0.0334 (0.091)	0.2329*** (0.016)	0.0327 (0.091)
Intercept	0.6585*** (0.005)	0.2506*** (0.030)	0.3391** (0.114)	0.0092 (0.688)	0.3386** (0.114)	0.0098 (0.688)	1.7937** (0.552)	0.2113 (2.837)	1.7919** (0.552)	0.2066 (2.837)
E(Y)	0.0007	0.0003	0.0007	0.0003	0.0007	0.0003	0.0013	0.0004	0.0013	0.0004
Age	N	N	Y	Y	Y	Y	Y	Y	Y	Y
Income	N	N	Y	Y	Y	Y	Y	Y	Y	Y
State	N	N	Y	Y	Y	Y	Y	Y	Y	Y
R-Squared	0.00	0.00	0.0003	0.0002	0.0003	0.0003	0.0006	0.0015	0.0006	0.0015
Adj. R-Squared	0.00	0.00	0.0003	0	0.0003	0	0.0006	-0.0003	0.0006	-0.0003
Observations	32.71M	330.36K	32.71M	330.36K	32.71M	330.36K	3.07M	31.49K	3.07M	31.49K

Note: Standard errors are reported in parentheses.

Coefficients and Standard Errors are multiplied by 1,000 for readability.

Statistical significance at the ten, five, and one percent levels is denoted by *, **, and ***, respectively.

Please refer to Appendix Table B1 for variable definitions.

Please refer to Appendix Table B3 for sample definitions.

Table 5. Impacts of the Legalization of Online Gambling (Venmo Sample)

This table examines the impact of online gambling legalization on individuals' online gambling spending. Columns (1) and (2) analyze the full sample of users. Columns (3) and (4) analyze users residing in states that changed their legalization status during the sample period. The dependent variables are *Gamble Vol_{it}*, which represents the dollar amount of online gambling spending by user *i* on Venmo during month *t*, and *Gamble Share_{it}*, which denotes the share of online gambling spending in total transaction volume for user *i* during month *t*. The key independent variable, *Legalized*, is an indicator equal to 1 if the user resides in a state where online gambling was legalized during the sample period. The regression is estimated using a Two-Way Fixed Effects (TWFE) model, which includes user fixed effects and year fixed effects.

	Full Gambling Sample		Legalized Gambling Sample	
	Gamble Vol	Gamble Share	Gamble Vol	Gamble Share
	(1)	(2)	(3)	(4)
Legalized	1.3145*** (0.0065)	0.0052*** (0.0000)	1.2712*** (0.0082)	0.0054*** (0.0000)
E(Y)	0.35	0.0012	0.65	0.002
R-Squared	0	0.0007	0	0.0012
Adj. R-Squared	0	0.0007	0	0.0012
Observations	1.82B	1.82B	337.07M	337.07M

Note: Standard errors are reported in parentheses.

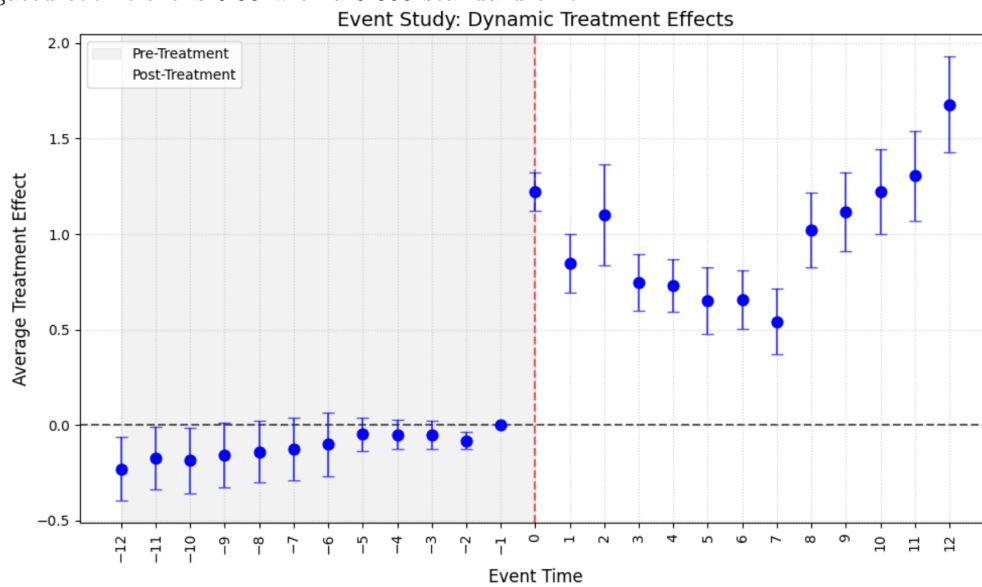
Statistical significance at the ten, five, and one percent levels is denoted by *, **, and ***, respectively.

Please refer to Appendix Table B1 for variable definitions.

Please refer to Appendix Table B3 for sample definitions.

Figure 1. CSDiD - Legalization Effect on Online Gambling Consumption (Venmo Sample)

This figure plots the dynamic effects of online gambling legalization on online gambling consumption using the Callaway and Sant’Anna difference-in-differences estimator. To improve computational efficiency, we use a 5% random sample of the full gambling natural experimental dataset based on Venmo. The treatment group consists of states that legalized online gambling between August 1, 2020, and March 31, 2023. The control group includes states that did not experience any online gambling legalization during the sample period. The sample includes a 12-month window before and after each state’s legalization event. Estimates are aggregated in an event study framework to show pre-trends and post-treatment dynamics. The aggregated coefficient is 0.99 with a 0.055 standard error.



Note: Confidence intervals are based on 95% significance levels. Standard errors are clustered at the state level. The control group consists of units that were never treated.

Table 6. Peer Legalization on Gambling Volume (Venmo Sample)

This table examines the impact of online gambling legalization in the states of individuals' friends on their gambling spending volumes. The analysis is restricted to a sample of Venmo users residing in states that legalized gambling and who had not engaged in gambling before the first legalization shock. The dependent variable, *Gamble Vol_{it}*, represents the total gambling volume of user *i* during month *t*. The key explanatory variable, *Sym Legalized_t*, is an indicator equal to 1 if gambling was legalized in the state of the user's first friend in their network. *Sym Legalized Adopted_t* is a binary variable capturing whether the user's first friend resides in a state where gambling was legalized and subsequently started gambling. To assess peer effects, *Sym Legalized_t* is interacted with *Sym Gamble*, which measures the number of gambling friends a user has, and *Sym Crypto*, which captures the number of friends involved in cryptocurrency. The regression is estimated using a Two-Way Fixed Effects (TWFE) model, which includes user fixed effects and year fixed effects.

	Gamble Vol			
	(1)	(2)	(3)	(4)
Sym Legalized	1.4623*** (0.0119)	1.0508*** (0.0128)	1.2429*** (0.0125)	0.9162*** (0.0132)
Sym Legalized X Sym Gamble		1.2585*** (0.0144)		1.1489*** (0.0146)
Sym Legalized X Sym Crypto			1.869*** (0.0315)	1.4518*** (0.032)
E(Y)	0.2756	0.2756	0.2756	0.2756
R-Squared	0	0	0	0
Adj. R-Squared	0	0	0	0
Observations	1.48B	1.48B	1.48B	1.48B

Note: Standard errors are reported in parentheses.

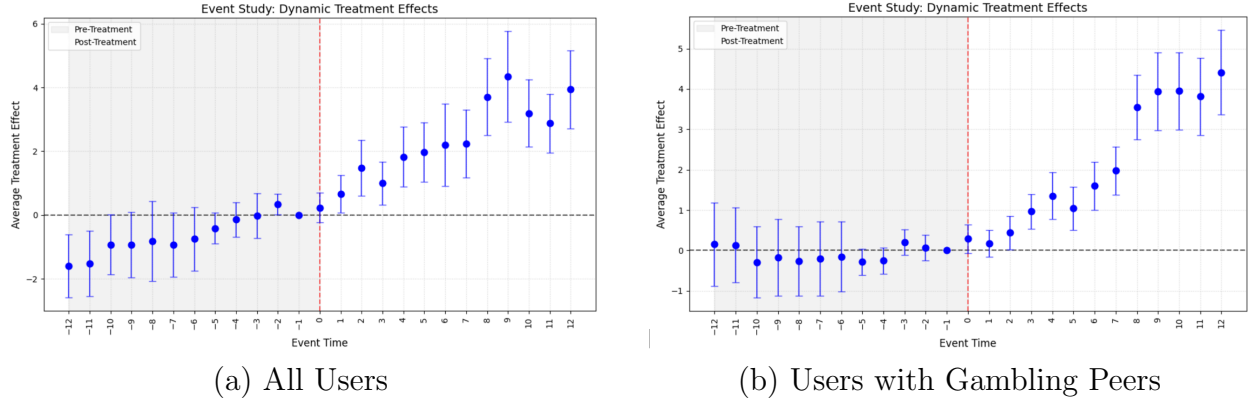
Statistical significance at the ten, five, and one percent levels is denoted by *, **, and ***, respectively.

Please refer to Appendix Table B1 for variable definitions.

Please refer to Appendix Table B3 for sample definitions.

Figure 2. CSDiD – Peer Legalization on Gambling Volume (Venmo Sample)

This figure shows the dynamic effects of peer’s online gambling legalization on one’s gambling behavior for Venmo users residing in early-legalizing states who had never gambled prior to the first legalization event. Panel A presents event-study estimates using a 10% random subsample, while Panel B reports estimates using the full eligible sample. Treatment timing is defined by each state’s legalization month, and effects are estimated using the Callaway and Sant’Anna (2021) difference-in-differences approach over a symmetric event window. For Panel A, the aggregated coefficient is 2.28 with a standard error of 0.29. For Panel B, the aggregated coefficient is 2.11 with a standard error of 0.196.



Note: Confidence intervals are based on 95% significance levels. Standard errors are clustered at the state level. The control group consists of units that were never treated.

Table 7. Treated Peers with Gamble (PayPal Sample)

This table examines whether individuals' online gambling behavior and their gambling peers influence their responses to the experiment. Columns (1) and (3) analyze the treatment group, while Columns (2) and (4) analyze the control group. The key independent variable, *Sym Treated*, represents the number of a user's friends who received the crypto incentive treatment in the 2021 Q1 experiment. *Sym Gamble Treated* measures the number of a user's gambling friends who were also treated in the experiment. *Sym Gamble* captures the number of a user's gambling friends who had already engaged in gambling prior to the start of the experiment. Additional covariates include *Sym Crypto*, which represents the number of friends involved in cryptocurrency before the experiment, and *Sym Degree*, which measures the overall number of a user's network connections. *Gambled* is an indicator for whether a user engaged in gambling before the experiment. Additional definitions can be found in Appendix. All regressions control for age, income, and state fixed effects where indicated.

	Treatment (1)	Control (2)	Treatment (3)	Control (4)
Sym Treated > 0	0.3559*** (0.0275)	0.0256 (0.1693)		
Sym Treated = 1			0.3552*** (0.0275)	0.0284 (0.1693)
Sym Treated > 1			0.1682** (0.0623)	0.5181 (0.3831)
Sym Gamble Treated > 0	-0.1198 (0.1452)	0.0676 (0.9276)	-0.0828 (0.1456)	-0.0338 (0.9303)
Gambled	0.7186*** (0.0485)	-0.3358 (0.2972)	0.7181*** (0.0485)	-0.3352 (0.2972)
Sym Crypto	1.4936*** (0.0678)	0.6694 (0.4151)	1.4730*** (0.0681)	0.7252 (0.4169)
Sym Gamble	-0.3438*** (0.0808)	-0.5028 (0.5092)	-0.3603*** (0.0810)	-0.4498 (0.5106)
Sym Degree	0.0854*** (0.0120)	0.0952 (0.0745)	0.1072*** (0.0136)	0.0367 (0.0850)
Log Num Txn	0.1778*** (0.0035)	0.0745*** (0.0213)	0.1776*** (0.0035)	0.0751*** (0.0213)
Intercept	0.3443** (0.1140)	0.0057 (0.6883)	0.3438** (0.1140)	0.0065 (0.6883)
E(Y)	0.0007	0.0003	0.0007	0.0003
Age	Y	Y	Y	Y
Income	Y	Y	Y	Y
State	Y	Y	Y	Y
R-Squared	0.0003	0.0003	0.0003	0.0003
Adj. R-Squared	0.0003	0.0000	0.0003	0.0000
Observations	32.71M	330.36K	32.71M	330.36K

Note: Coefficients and standard errors are multiplied by 1,000 for readability.

Statistical significance at the ten, five, and one percent levels is denoted by *, **, and ***, respectively.

Please refer to Appendix Table B1 for variable definitions.

Please refer to Appendix Table B3 for sample definitions.

Table 8. Peer Diffusion of Crypto Spending Behavior Based on Legalization Natural Experiment (Venmo Sample)

This table examines the impact of online gambling legalization on users' cryptocurrency spending behavior. Columns (1)–(4) report estimates for the full sample of Venmo users, while Columns (5)–(8) analyze the subsample of Venmo users who ever purchased cryptocurrency during the sample period. The dependent variables are *Crypto Vol_{it}*, defined as the dollar amount of cryptocurrency purchased by user *i* in month *t*. The key explanatory variable, *Legalized*, equals 1 if the user resides in a state where online gambling was legalized during the sample period. Interaction terms capture heterogeneity in peer-based responses: *Legalized X Sym Gamble* measures whether users with more symmetric (mutual) gambling friendships adjust their crypto spending differently following legalization; *Legalized X Sym Crypto* measures whether users with more symmetric (mutual) crypto friendships adjust their crypto spending differently following legalization; *Legalized X Sym Gamble = 1* and *Legalized X Sym Gamble > 1* differentiate between users with exactly one versus more than one gambling friend. All regressions are estimated using a Two-Way Fixed Effects (TWFE) specification that includes user fixed effects and year fixed effects.

	Full Gambling Sample				Crypto User Sample			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Legalized	-0.0225*** (0.0041)	0.0002 (0.0042)	0.0014 (0.0042)	-0.0010 (0.0042)	-2.3888*** (0.4135)	-1.4644*** (0.4326)	-1.2522** (0.4472)	-1.8282*** (0.4382)
Legalized X Sym Gamble		-0.1809*** (0.0075)		-0.1847*** (0.0076)		-3.4217*** (0.4707)		-3.8318*** (0.4772)
Legalized X Sym Crypto				0.0568** (0.0214)				7.8664*** (1.5131)
Legalized X Sym Gamble = 1			-0.2242*** (0.0163)				-6.1735*** (1.3134)	
Legalized Sym Gamble >1			-0.4430*** (0.0256)				-9.2235*** (1.7319)	
E(Y)	0.191	0.191	0.191	0.191	19.4	19.4	19.4	19.4
R-Squared	0	0	0	0	0	0	0	0
Adj. R-Squared	0	0	0	0	0	0	0	0
Observations	1.82B	1.82B	1.82B	1.82B	17.91M	17.91M	17.91M	17.91M

Note: Standard errors are reported in parentheses.

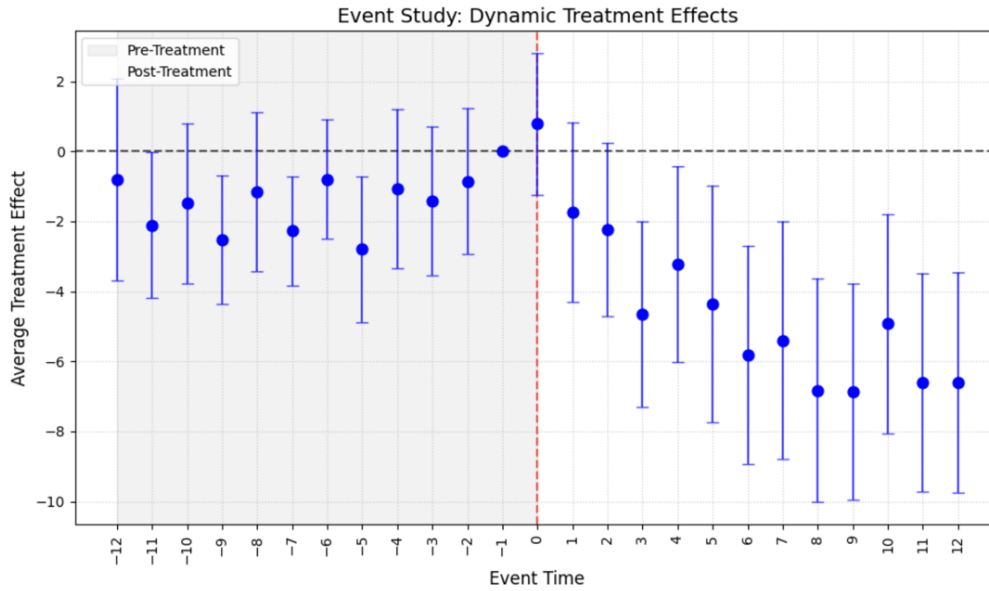
Statistical significance at the ten, five, and one percent levels is denoted by *, **, and ***, respectively.

Please refer to Appendix Table B1 for variable definitions.

Please refer to Appendix Table B3 for sample definitions.

Figure 3. CSDiD - Legalization Effect on Crypto Purchase (Venmo Sample)

This figure plots the dynamic effects of online gambling legalization on crypto purchases of crypto users using the Callaway and Sant'Anna difference-in-differences estimator. We use the full data sample of Venmo users who ever purchased crypto in our sample period. The treatment group consists of states that legalized online gambling between August 1, 2020, and March 31, 2023. The control group includes states that did not experience any online gambling legalization during the sample period. The sample includes a 12-month window before and after each state's legalization event. Estimates are aggregated in an event study framework to show pre-trends and post-treatment dynamics. The aggregated coefficient is -4.5 with a standard error of 1.67.



Note: Confidence intervals are based on 95% significance levels. Standard errors are clustered at the state level. The control group consists of units that were never treated.

Table 9. Impact of Peer Legalization on Crypto Spending (Venmo Sample)

This table examines the impact of online gambling legalization in the states of individuals' friends on their cryptocurrency purchase volumes. The analysis is restricted to Venmo users residing in states that did not experience a gambling legalization shock and who had not engaged in gambling prior to the first legalization event. The dependent variable, *Crypto Vol_{it}*, represents the dollar amount of cryptocurrency purchased by user *i* during month *t*. The key explanatory variable, *Sym Legalized_t*, equals 1 if gambling was legalized in the state of the user's first friend in their network. The interaction term *Sym Legalized X Sym Gamble* assesses whether having more gambling-oriented peers amplifies the effect of gambling legalization on a user's cryptocurrency purchasing behavior. Similarly, the interaction *Sym Legalized X Sym Crypto* examines whether exposure to friends who participate in cryptocurrency activity modifies the user's crypto response to online gambling legalization. All regressions are estimated using a Two-Way Fixed Effects (TWFE) model that includes user fixed effects and year fixed effects.

	Crypto Vol			
	(1)	(2)	(3)	(4)
Sym Legalized	-0.2328*** (0.0073)	-0.177*** (0.0079)	-0.2405*** (0.0077)	-0.1891*** (0.0081)
Sym Legalized X Sym Gamble		-0.1707*** (0.0089)		-0.1806*** (0.0090)
Sym Legalized X Sym Crypto			0.0651*** (0.0194)	0.1307*** (0.0197)
E(Y)	0.189	0.189	0.189	0.189
R-Squared	0	0	0	0
Adj. R-Squared	0	0	0	0
Observations	1.48B	1.48B	1.48B	1.48B

Note: Standard errors are reported in parentheses.

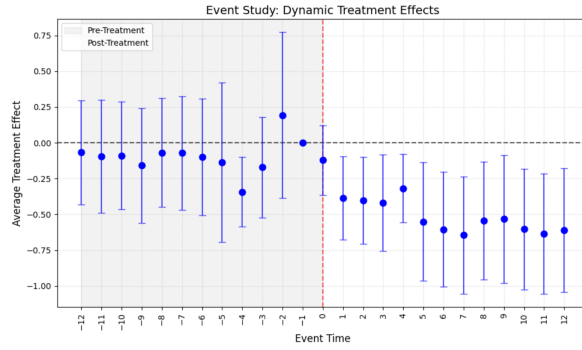
Statistical significance at the ten, five, and one percent levels is denoted by *, **, and ***, respectively.

Please refer to Appendix Table B1 for variable definitions.

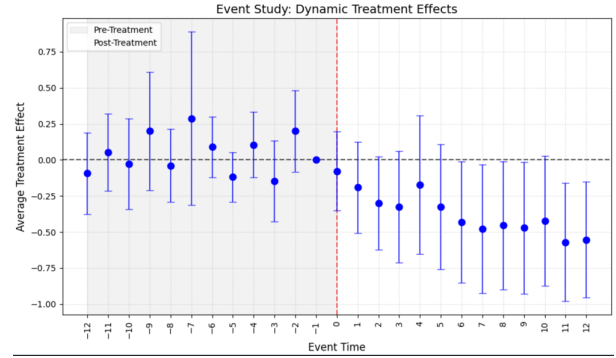
Please refer to Appendix Table B3 for sample definitions.

Figure 4. CSDiD – Peer Legalization on Crypto Volume (Venmo Sample)

This figure shows the dynamic effects of peer’s online gambling legalization on one’s crypto spending for Venmo users residing in early-legalizing states who had never gambled prior to the first legalization event. Panel A presents event-study estimates using a 10% random subsample of the full sample, while Panel B reports estimates using the full eligible sample of users with at least 1 gambling peer. Treatment timing is defined by each state’s legalization month, and effects are estimated using the Callaway and Sant’Anna (2021) difference-in-differences approach over a symmetric event window. For Panel A, the aggregated coefficient is -0.49 with a standard error of 0.17. For Panel B, the aggregated coefficient is -0.37 with a standard error of 0.2.



(a) All Users



(b) Users with Gambling Peers

Note: Confidence intervals are based on 95% significance levels. Standard errors are clustered at the state level. The control group consists of units that were never treated.

Table 10. Impact of Online Gambling Legalization on Retail Transaction (Venmo Sample)

This table examines the impact of online gambling legalization on individuals' total transaction volumes. Columns (1)–(4) analyze total transaction volumes for the full Venmo sample. The dependent variable, *Retail Vol_{it}*, represents the retail transaction volume for user *i* during month *t*. The key independent variable, *Legalized*, is an indicator equal to 1 if online gambling was legalized in an individual's state. To assess peer effects, *Legalized* is interacted with *Sym Gamble*, which measures the number of gambling friends a user has. Additional interaction terms, *Legalized X Sym Gamble = 1* and *Legalized X Sym Gamble > 1*, differentiate between having exactly one and more than one gambling friend. The interaction term *Legalized X Sym Crypto* evaluates whether exposure to crypto-active peers moderates the effect of gambling legalization on users' overall transaction volumes. All regressions are estimated using a Two-Way Fixed Effects (TWFE) model that includes user fixed effects and year fixed effects.

	Retail Spending Volume			
	(1) All	(2) All	(3) All	(4) All
Legalized	0.1115*** (0.0116)	0.1794*** (0.0119)	0.135*** (0.0121)	0.1943*** (0.012)
Legalized X Sym Gamble		-0.5426*** (0.0215)		-0.4953*** (0.0218)
Legalized X Sym Crypto				-0.7089*** (0.0613)
Legalized X Sym Gamble = 1			0.0837 (0.0466)	
Legalized X Sym Gamble > 1			-1.219*** (0.0733)	
E(Y)	8.07	8.07	8.07	8.07
R-Squared	0	0	0	0
Adj. R-Squared	0	0	0	0
Observations	1.82B	1.82B	1.82B	1.82B

Note: Standard errors are reported in parentheses.

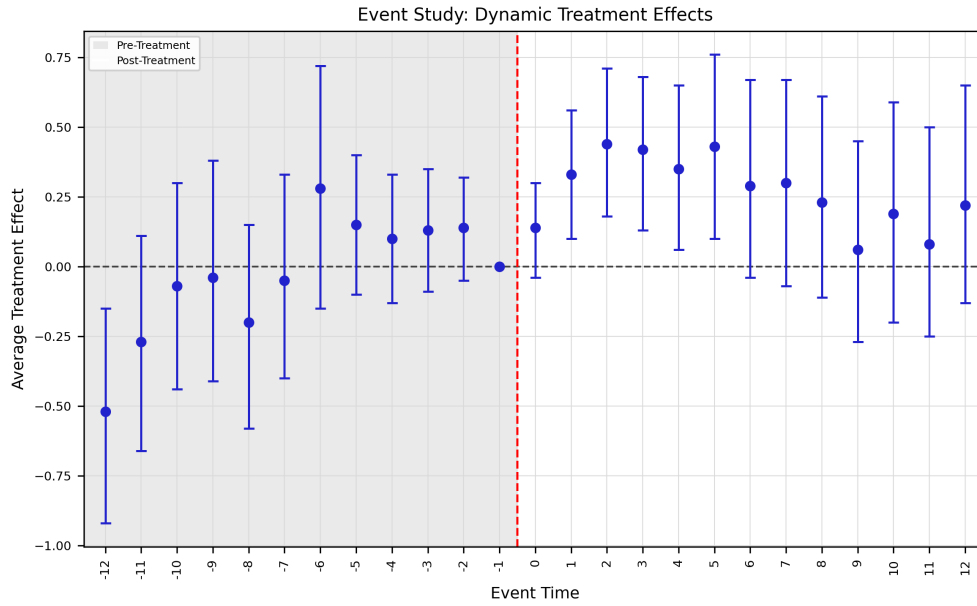
Statistical significance at the ten, five, and one percent levels is denoted by *, **, and ***, respectively.

Please refer to Appendix Table B1 for variable definitions.

Please refer to Appendix Table B3 for sample definitions.

Figure 5. CSDiD - Legalization Effect on Retail Transaction

This figure plots the dynamic effects of online gambling legalization on retail spending of Venmo users using the Callaway and Sant'Anna difference-in-differences estimator. We use the full gambling sample. The treatment group consists of states that legalized online gambling between August 1, 2020, and March 31, 2023. The control group includes states that did not experience any online gambling legalization during the sample period. The sample includes a 12-month window before and after each state's legalization event. Estimates are aggregated in an event study framework to show pre-trends and post-treatment dynamics.



Note: Confidence intervals are based on 95% significance levels. Standard errors are clustered at the state level. The control group consists of units that were never treated.

A Appendix A: Additional Analyses

Table A1: Other Crypto Platform Users (PayPal Sample)

This table reports summary statistics for users of other crypto platforms (OCP). OCP users are defined as individuals who have made cryptocurrency purchases from other crypto platforms using PayPal during the sample period. The table presents key transaction and demographic characteristics, including network connectivity (symmetric degree), transaction activity, and income and age distribution. The second column reports standard deviations for each variable.

	OCP Users	
	N=666K	
	Mean	SD
Symmetric Degree	0.2697	0.7866
Number of Total Transactions Per Year	65.6802	81.4137
Total Transaction Volume Per Year	4,899.49	8,277.90
Number of P2P Transactions Per Year	7.4411	21.5022
P2P Transaction Volume Per Year	1,265.93	4,275.39
Number of Retail Transactions Per Year	53.6152	70.6722
Retail Transaction Volume Per Year	3,101.04	4,736.50
Age: 50+	0.1609	0.3674
Age: 30–49	0.5068	0.5000
Age: 18–29	0.3324	0.4711
Income: >\$125K	0.1490	0.3561
Income: \$50–125K	0.4747	0.4994
Income: <\$50K	0.3763	0.4844

““

Table A2: Balance Table for First Campaign

	Trt. Mean	Trt. SD	Ctl. Mean	Ctl. SD	p-Value
Symmetric Degree	0.1568	0.5792	0.1568	0.577	0.9816
Symmetric Crypto	0.0049	0.0720	0.0049	0.0727	0.7329
Symmetric Coinbase	0.0025	0.0505	0.0025	0.0512	0.8084
Symmetric Gamble	0.0049	0.0802	0.0046	0.0777	0.1173
Number of Total Transactions Per Year	30.8857	53.2516	30.9718	53.7577	0.3551
Total Transaction Volume Per Year	1,910.85	3,405.29	1,907.40	3,393.29	0.5619
Number of P2P Transactions Per Year	4.5961	14.3529	4.5926	14.2182	0.8901
P2P Transaction Volume Per Year	623.2237	2,102.35	621.2925	2,074.17	0.5993
Number of Retail Transactions Per Year	24.4493	46.9384	24.5390	47.4933	0.2745
Retail Transaction Volume Per Year	1,159.90	2,237.19	1,158.60	2,233.31	0.7397
Fraction of People Ever Gambled	0.0098	0.0987	0.0099	0.0990	0.8008
Fraction of People Ever used Coinbase	0.0077	0.0876	0.0076	0.0867	0.3037
Age: 50+	0.2548	0.4358	0.2551	0.4359	0.7189
Age: 30-49	0.4286	0.4949	0.4293	0.4950	0.4300
Age: 18-29	0.3165	0.4651	0.3156	0.4647	0.2392
Income: >\$125K	0.1317	0.3382	0.1311	0.3375	0.3385
Income: \$50-125K	0.4513	0.4976	0.4509	0.4976	0.6149
Income: <\$50K	0.4170	0.4931	0.4180	0.4932	0.2443

In this table we present the balance table of variables for the treatment and control groups of the 2021 Q1 experiment. p-Values of difference tests on means are reported.

Table A3: Balance Table for Second Campaign

	Trt. Mean	Trt. SD	Ctl. Mean	Ctl. SD	p-Value
Symmetric Degree	0.3616	0.9141	0.3621	0.9130	0.6789
Symmetric Crypto	0.0119	0.1130	0.0122	0.1141	0.0626
Symmetric Coinbase	0.0061	0.0800	0.0060	0.0794	0.4926
Symmetric Gamble	0.0133	0.1381	0.0133	0.1390	0.7314
Number of Total Transactions Per Year	61.1328	73.4081	61.1425	73.7969	0.9218
Total Transaction Volume Per Year	3,528.44	4,563.27	3,535.24	4,582.95	0.2659
Number of P2P Transactions Per Year	9.1278	20.7429	9.1285	20.3342	0.9807
P2P Transaction Volume Per Year	1,213.72	2,919.33	1,220.96	2,966.41	0.0644
Number of Retail Transactions Per Year	48.3296	65.8871	48.3410	66.5282	0.8969
Retail Transaction Volume Per Year	2,066.20	2,954.77	2,066.56	2,949.29	0.9283
Fraction of People Ever Gambled	0.0247	0.1551	0.0249	0.1560	0.1802
Fraction of People Ever used Coinbase	0.0150	0.1215	0.0149	0.1213	0.7361
Age: 50+	0.2122	0.4088	0.2128	0.4093	0.2311
Age: 30-49	0.4949	0.5000	0.4944	0.5000	0.4572
Age: 18-29	0.2929	0.4551	0.2927	0.4550	0.7956
Income: >\$125K	0.1284	0.3345	0.1284	0.3346	0.9339
Income: \$50-125K	0.4382	0.4962	0.4390	0.4963	0.2051
Income: <\$50K	0.4334	0.4955	0.4325	0.4954	0.1852

In this table we present the balance table of variables for the treatment and control groups of the 2021 Q2 experiment. p-Values of difference tests on means are reported.

Table A4: Adoption of Crypto in the Second Incentive Experiment

	Full Experiment Sample			Attentive Users	
	(1)	(2)	(3)	(4)	(5)
Treated	0.1459*** (0.037)	0.1459*** (0.037)	0.1461*** (0.037)	0.3007 (0.183)	0.3003 (0.183)
Treated Q1	-0.1108*** (0.017)	-0.1109*** (0.017)	-0.1090*** (0.017)	-1.2764*** (0.107)	-1.2747*** (0.107)
Sym Crypto	0.7693*** (0.072)			1.4723*** (0.359)	
Sym Crypto = 1		1.6120*** (0.401)	1.6061*** (0.401)		3.7398* (1.897)
Sym Crypto >1		0.7723*** (0.078)	0.7692*** (0.078)		1.4422*** (0.389)
Sym Degree	0.0099 (0.009)	0.0102 (0.009)	0.0092 (0.009)	-0.0426 (0.048)	-0.0503 (0.049)
Was Gamble			0.6167*** (0.053)		1.2653*** (0.278)
Has Sym Gamble			-0.0627 (0.079)		0.0778 (0.414)
Log Num Txn	0.0262*** (0.007)	0.0262*** (0.007)	0.0215** (0.007)	0.0378 (0.033)	0.0283 (0.033)
Intercept	0.7431*** (0.204)	0.7431*** (0.204)	0.7497*** (0.204)	3.2863** (1.082)	3.2950** (1.082)
Control Mean	0.0006	0.0006	0.0006	0.0011	0.0011
Age	Y	Y	Y	Y	Y
Income	Y	Y	Y	Y	Y
State	Y	Y	Y	Y	Y
R-Squared	0	0	0	0.0003	0.0004
Adj. R-Squared	0	0	0	0.0003	0.0003
Observations	12.30M	12.30M	12.30M	930.02K	930.02K

Note: Coefficients and Standard Errors are multiplied by 1,000 for readability.

Standard errors are at the person level and reported in parentheses.

Statistical significance at the ten, five, and one percent levels is denoted by *, **, and ***, respectively.

Please refer to Appendix Table B1 for additional variable definitions.

Table A5: Age Heterogeneity of Treated Peers

	Full Experiment Sample		High Age Sample		Mid Age Sample		Low Age Sample	
	Trt.	Ctl.	Trt.	Ctl.	Trt.	Ctl.	Trt.	Ctl.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sym Treated >0	0.3735*** (0.037)	0.3217 (0.227)	0.6007*** (0.086)	-0.1290 (0.591)	0.4660*** (0.074)	-0.1372 (0.373)	0.1719*** (0.052)	0.3049 (0.386)
High Age Sym Treated >0	0.0676 (0.052)	-0.8394** (0.321)	0.0194 (0.100)	-0.4990 (0.694)	0.1240 (0.089)	-0.1750 (0.452)	-0.1346 (0.096)	-1.3268 (0.694)
Mid Age Sym Treated >0	-0.0497 (0.042)	-0.3056 (0.257)	-0.3321*** (0.095)	0.9555 (0.656)	-0.0434 (0.079)	0.3570 (0.397)	-0.0340 (0.066)	-1.1425* (0.4824)
Sym Crypto	1.4827*** (0.068)	0.6108 (0.414)	1.0425*** (0.137)	-0.5698 (0.959)	1.8274*** (0.106)	-0.2369 (0.523)	1.1475*** (0.116)	2.3724** (0.848)
Sym Degree	0.0744*** (0.012)	0.1064 (0.074)	0.0519* (0.024)	0.0967 (0.161)	0.0186 (0.018)	-0.0092 (0.091)	0.1892*** (0.022)	0.3284* (0.167)
Log Num Txn	0.1822*** (0.003)	0.0723*** (0.021)	0.1494*** (0.005)	0.0813* (0.037)	0.2072*** (0.006)	0.0245 (0.029)	0.1720*** (0.006)	0.1326** (0.046)
Intercept	0.3388** (0.114)	-0.0035 (0.688)	0.0220 (0.172)	-0.1133 (1.153)	0.5047** (0.191)	-0.0355 (0.930)	0.3805 (0.210)	-0.2335 (1.558)
E(Y)	0.0007	0.0003	0.0005	0.0002	0.0009	0.0002	0.0007	0.0004
Age	Y	Y						
Income	Y	Y	Y	Y	Y	Y	Y	Y
State	Y	Y	Y	Y	Y	Y	Y	Y
R-Squared	0.0003	0.0003	0.0002	0.0009	0.0003	0.0004	0.0003	0.0008
-Adj. R-Squared	0.0003	0	0.0002	0.0002	0.0003	0	0.0003	0.0002
Observations	32.71M	330.36K	8.33M	84.28K	14.02M	141.83K	10.35M	104.25K

Note: Coefficients and Standard Errors are multiplied by 1,000 for readability.

Standard errors are at the person level and reported in parentheses.

Statistical significance at the ten, five, and one percent levels is denoted by *, **, and ***, respectively.

High age users are >50 years old, middle age 30 to 49 years old, low age 18 to 29 years old.

Please refer to Appendix Table B1 for variable definitions.

Table A6: Income Heterogeneity of Treated Peers

	Full Experiment Sample		High Income Sample		Mid Income Sample		Low Income Sample	
	Trt. (1)	Ctl. (2)	Trt. (3)	Ctl. (4)	Trt. (5)	Ctl. (6)	Trt. (7)	Ctl. (8)
Sym Treated >0	0.6850*** (0.033)	0.1744 (0.200)	0.5529*** (0.080)	-1.7813*** (0.532)	0.5365*** (0.047)	-0.1825 (0.306)	0.6610*** (0.054)	0.4394 (0.317)
High Income Sym Treated >0	-0.7639*** (0.060)	-0.2391 (0.372)	-0.4682*** (0.096)	2.1719*** (0.638)	-0.4588*** (0.080)	0.0070 (0.519)	-0.9852*** (0.135)	-1.2403 (0.807)
Medium Income Sym Treated >0	-0.6445*** (0.039)	-0.2797 (0.242)	-0.6305*** (0.092)	1.8406** (0.612)	-0.3371*** (0.054)	0.2239 (0.346)	-0.7642*** (0.070)	-0.7156 (0.416)
Sym Crypto	1.4424*** (0.068)	0.6203 (0.414)	0.7658*** (0.140)	-0.9849 (1.019)	0.9138*** (0.091)	-0.0996 (0.577)	2.0131*** (0.118)	1.4912* (0.684)
Sym Degree	0.1169*** (0.012)	0.0895 (0.074)	0.0848*** (0.022)	0.2979* (0.146)	0.0603*** (0.015)	-0.0832 (0.099)	0.1746*** (0.022)	0.1837 (0.134)
Log Num Txn	0.1813*** (0.003)	0.0724*** (0.021)	0.1005*** (0.006)	0.0034 (0.040)	0.1376*** (0.004)	0.0635* (0.028)	0.2565*** (0.007)	0.1068** (0.039)
Intercept	0.3283** (0.114)	0.0068 (0.688)	-0.2609 (0.241)	0.0458 (1.866)	-0.0190 (0.152)	-0.1088 (0.921)	0.1405 (0.197)	-0.1016 (1.157)
E(Y)	0.0007	0.0003	0.0003	0.0001	0.0005	0.0002	0.0011	0.0004
Age	Y	Y	Y	Y	Y	Y	Y	Y
Income	Y	Y						
State	Y	Y	Y	Y	Y	Y	Y	Y
R-Squared	0.0003	0.0003	0.0001	0.0012	0.0001	0.0003	0.0003	0.0006
Adj. R-Squared	0.0003	0	0.0001	0	0.0001	-0.0001	0.0003	0.0002
Observations	32.71M	330.36K	4.31M	43.32K	14.76M	148.95K	13.64M	138.09K

Note: Coefficients and Standard Errors are multiplied by 1,000 for readability.

Standard errors are at the person level and reported in parentheses.

Statistical significance at the ten, five, and one percent levels is denoted by *, **, and ***, respectively.

High-income users have incomes >\$125K, middle-income users \$50-125K and low-income users <\$50K.

Please refer to Appendix Table B1 for additional variable definitions.

Table A7: Peer Diffusion of Crypto through Other Crypto Platforms (OCP) (PayPal Sample)

This table examines whether individuals' usage of Other Crypto Platforms (OCP) influences their response to the treatment and whether the experiment generates a spillover effect on the adoption of other crypto platforms. Columns (1) to (3) analyze the adoption of *Adopted Crypto*, defined as an indicator variable equal to 1 if a user adopts cryptocurrency on PayPal within the first two months after the experiment start. Columns (4) and (6) analyze *Adopted OCP*, which indicates whether a user begins purchasing cryptocurrency on other crypto platforms within the same period. Column (7) examines *Only Adopted OCP*, which takes the value of 1 if a user starts purchasing crypto exclusively on other crypto platforms without making any purchases on PayPal. The key independent variable, *Treated*, indicates whether the user was assigned to receive the crypto incentive. *Sym Treated* captures whether a user's symmetric (mutual) connections were also assigned to the treatment. *OCP* is a binary indicator for prior other crypto platforms usage, while *Sym OCP* measures the number of symmetric connections who are users of other crypto platforms. Additional definitions can be found in Appendix. All regressions control for age, income, and state fixed effects where indicated.

	Adopted Crypto			Adopted OCP			Only Adopted OCP
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Treated	0.4455*** (0.047)	0.4454*** (0.047)	0.4454*** (0.047)	0.1012** (0.038)	0.0980** (0.038)	0.0980* (0.038)	0.0955* (0.037)
Sym Treated			0.0456 (0.024)			-0.0509** (0.019)	
OCP	0.7023 (0.537)	0.7026 (0.537)	0.7223 (0.538)	-0.6570 (0.434)	-0.6464 (0.434)	-0.6317 (0.435)	-0.6232 (0.426)
OCP X Treated	0.2344 (0.540)	0.2340 (0.540)	0.2321 (0.540)	-0.1027 (0.436)	-0.1134 (0.437)	-0.1151 (0.437)	-0.1108 (0.428)
Sym OCP X Treated		0.0412 (0.914)	0.0408 (0.914)		1.3421 (0.739)	1.3429 (0.739)	1.3331 (0.725)
OCP X Sym Treated			-0.1499 (0.123)			-0.1111 (0.099)	
Sym Crypto	1.3558*** (0.067)	1.3558*** (0.067)	1.3785*** (0.068)	0.2656*** (0.054)	0.2657*** (0.054)	0.2391*** (0.055)	0.2497*** (0.053)
Sym OCP	-0.0193 (0.094)	-0.0601 (0.910)	-0.0538 (0.910)	0.7306*** (0.076)	-0.5977 (0.735)	-0.5990 (0.735)	-0.5700 (0.721)
Sym Degree	0.1776*** (0.009)	0.1776*** (0.009)	0.1552*** (0.015)	-0.0307*** (0.007)	-0.0307*** (0.007)	-0.0040 (0.012)	-0.0313*** (0.007)
Log Num Txn	0.1798*** (0.003)	0.1798*** (0.003)	0.1797*** (0.003)	0.2182*** (0.003)	0.2182*** (0.003)	0.2182*** (0.003)	0.2115*** (0.003)
Intercept	-0.0990 (0.122)	-0.0989 (0.122)	-0.0993 (0.122)	0.0441 (0.099)	0.0473 (0.099)	0.0477 (0.099)	0.0621 (0.097)
Control Mean	0.0003	0.0003	0.0003	0.00037	0.00037	0.00035	0.00035
Age	Y	Y	Y	Y	Y	Y	Y
Income	Y	Y	Y	Y	Y	Y	Y
State	Y	Y	Y	Y	Y	Y	Y
R-Squared	0.0003	0.0003	0.0003	0.0003	0.0003	0.0003	0.0002
Adj. R-Squared	0.0003	0.0003	0.0003	0.0002	0.0002	0.0002	0.0002
Observations	33.04M	33.04M	33.04M	33.04M	33.04M	33.04M	33.04M

Table A8: Summary Statistics, PayPal Gambling Legalization User Transactions and Networks

This table displays the summary statistics for our main variables. We display user characteristics of the sub-samples of the gamble natural experiment.

	Obs	Mean	P25	P50	P75	P95	P99
Gamble Legalization Sample							
Number of Total Transactions Per Year	72.42M	32.2	2	12	40	129	246
Number of P2P Transactions Per Year	72.42M	3.48	0	0	2	17	50
Number of Retail Transactions Per Year	72.42M	27.1	1	8	33	114	223
Fraction of People Ever Gambled	72.42M	0.0168	0	0	0	0	1
Fraction of People Ever used Coinbase	72.42M	0.0123	0	0	0	0	1
Fraction of People Ever used Crypto	72.42M	0.0145	0	0	0	0	1

B Appendix B: Definitions and Additional Context

Table B1: Variable Description

Variable	Description
Experiment Variables	
Adopted Crypto	A binary indicator variable equal to 1 if the user purchased cryptocurrency on PayPal within two months of the experiment’s start date, and 0 otherwise.
Adopted OCP	A binary indicator variable equal to 1 if the user made a purchase on other crypto platforms via PayPal within two months of the experiment’s start date, and 0 otherwise.
Treated	A binary indicator variable equal to 1 if the user received the cryptocurrency incentive as part of the 2021 Q1 experiment, and 0 otherwise.
Sym Degree	The number of individuals with whom the user reciprocally exchanged payments on PayPal.
Sym Crypto	The number of friends who had purchased crypto before the experiment.
Sym OCP	The number of friends who had purchased from other crypto platforms before the experiment.
Sym Gamble	The number of friends who had gambled before the experiment.
Log Num Txn	The natural logarithm of the total number of transactions made by the user in the year preceding the experiment.
Was Gamble	A binary indicator variable equal to 1 if the user engaged in gambling activities prior to the experiment, and 0 otherwise.
Was OCP	A binary indicator variable equal to 1 if the user made purchases on other crypto platforms before the experiment, and 0 otherwise.
Sym Treated	The number of friends who were treated in the experiment.
Top Sym Freq Treated	The number of closest friends (by transactions) treated in Q1.
Top Sym Ovlp Treated	The number of closest friends (by overlaps) treated in Q1.
Variants	
Treated Q1/Q2/Both	A binary indicator variable equals to 1 if the user received treatment in Q1/Q2/both, and 0 otherwise.
Gamble Sym Treated	The number of friends who ever gambled before the experiment and were treated.
Sym Crypto/Gamble ≥ 1	A binary indicator variable equals to 1 if the number of crypto or gamble friends is equal to/higher than 1, and 0 otherwise.

Table B1: Variable Description

Variable	Description
Panel Variables	
Gamble/Crypto Volume	The total dollar value that user i spends on online gambling or Venmo's crypto platform in month t .
Retail Transaction Volume	The total dollar value that user i spends on Venmo with good and service merchants except for online gambling and crypto purchasing in month t .
Legalized	A binary indicator variable equal to 1 once the user's state legalized online gambling in month t , and 0 before the legalization.
Sym Legalized	A binary indicator variable equal to 1 once any of the user's friends' state legalized online gambling in month t , and 0 before the legalization.
Sym Crypto	The number of friends who ever purchased crypto in the baseline period (Before August 2021).
Sym Gamble	The number of friends who ever gambled in the baseline period (Before August 2021).
Variants	
Sym Crypto/Gamble ≥ 1	A binary indicator variable equals to 1 if the number of crypto or gamble friends is equal to/higher than 1, and 0 otherwise.

Table B2: Launch Dates

State	Launch Date
Nevada	2010-01-01
Delaware	2012-06-28
New Jersey	2018-06-06
West Virginia	2018-12-27
Pennsylvania	2019-05-28
Iowa	2019-08-15
Rhode Island	2019-09-14
Indiana	2019-10-03
New Hampshire	2019-12-30
Colorado	2020-05-01
Illinois	2020-06-18
Tennessee	2020-11-01
Virginia	2021-01-21
Michigan	2021-01-22
Wyoming	2021-09-01
Arizona	2021-09-09
New York	2022-01-08
Louisiana	2022-01-28
Kansas	2022-09-01
Maryland	2022-11-23
Ohio	2023-01-01
Massachusetts	2023-03-10

Table B3: Sample Description

Sample Name	Definition
Experiment	
Full Experiment Sample	This sample consists the PayPal users who were selected in the first PayPal marketing experiment.
Attentive Users	This sample consists the PayPal users who were selected in the first PayPal marketing experiment and who opened the marketing emails.
Panel	
Full Gambling Sample	This sample consists of all Venmo users who created their accounts prior to August 2021, ensuring their entire activity history is observable during the study period. The account creation date restriction applies uniformly across all samples.
Legalized Gambling Sample	This sample consists Venmo users residing in states where a legalization shock to online gambling occurred during the study period. These are states that changed their legal status for gambling.