Competing Network Effects: Evidence from Crypto and Gambling Adoption*

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March 20, 2025

Abstract

We study the impact of peer effects on the adoption of new retail financial products such as cryptocurrencies and gambling. Using transaction level data from the PayPal's payment platform, we document a new crowd-out effect within networks, if peers with multiple interests compete for the limited attention or time of their friends. We identify two exogenous shocks to the exposure of peers to cryptocurrency and gambling adoption to show that peers with interests in cryptocurrencies (gambling) amplify the adoption of crypto (gambling) among their peers. However, "pre-existing" peer interests in one of these activities impede (and partially crowd out) the adoption of the other activity.

*We are indebted to Xinrong Yao, Xin Xiong and Ziyi Zeng for outstanding research assistance. We gratefully acknowledge funding from PayPal. Institutional Review Board (IRB) approvals were obtained from MIT.

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1 Introduction

A large literature in economics and finance highlights the role of peer interactions in the adoption of new products, technologies, or services, as well as ultimate economic and financial outcomes; for a summary of examples in finance, see Kuchler and Stroebel (2021). However, little is still known about the exact mechanisms through which these peer effects operate.

Individuals are typically part of many, often overlapping peer networks that might help reinforce the adoption of different actions or products, but might also compete for the participation and attention of network members. When there is a wide variety of behaviors that peers can engage in, different peers might be competing for limited time, attention, or financial budgets of network members. In this paper, we aim to shed light on this aspect of peer effects that, to our knowledge, has not been studied in the literature.

The difficulty in studying these competing network effects lies in the data requirements. First, we need to observe a range of different interactions of individuals to map out their peer networks. Second, we need data on the various actions or behaviors that an individual's peers engage in. And finally, we need to have (quasi) exogenous shocks to the adoption of different behaviors by peers to differentiate the peer effect from assortative matching in peer networks, see for example Goldsmith-Pinkham and Imbens (2011) and Bramoulle et al (2020).

The specific application we analyze in this paper is the role of peer effects in the adoption of new financial products, in particular, cryptocurrencies and gambling. These have been two of the fastest growing new activities among retail investors in the US over the last decade. Trading in cryptocurrencies and gambling are also often compared to each other, since both are risk-taking activities, and participation in them is seen to have a significant social networks component. At the same time, they both require financial and often significant time commitment, and require users to engage on different platforms. We study the role of peer effects in the adoption of these new products, and in particular the degree to which peers with divergent interests compete for the attention of their friends and crowd out alternative activities. For this analysis, we take a person's peer network as given but look for shocks to the propensity of their friends to either engage in gambling or crypto trading; and how (or whether) these shocks spill over to their network peers.

We show that peers with interests in cryptocurrencies (gambling) amplify the adoption of crypto (gambling) among their peers. However, "pre-existing" peer interests in one of these activities impede (and partially crowds out) the adoption of the other activity. In other words, if a person's peers are already engaged in gambling, the person is less likely to adopt cryptocurrencies even when they become available (and vice versa for gambling). These

results suggest that people have limited attention or time budgets for different activities and that peers across different types of activities compete for their friends' attention to engage in like-minded activities.

To obtain these results and address the above-described data challenges, we use (anonymized) transaction level data from PayPal, one of the largest payment systems in the US. Using data from the entire PayPal customer base in the US, we first identify a user's social network as their "payment friends", the set of people they share peer-to-peer transactions with.[1] This is a particularly demanding definition of a social network, but one that is perhaps more salient for determining financial and economic transactions and outcomes.

To analyze the role of financial peers in the adoption of cryptocurrencies and 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 (Bitcoin, Ethereum and BitcoinCash) on its platform in the fall of 2020, PayPal conducted several large-scale marketing experiments providing financial incentives to PayPal customers to encourage the purchase of cryptocurrencies through PayPal.[2]

We first use these marketing campaigns to confirm that there are general peer effects in the adoption of cryptocurrencies on the PayPal network. We show that users who received randomized incentives are more likely to adopt and trade cryptocurrencies. This is akin to a "first-stage" analysis confirming that the marketing experiment had a positive effect on adoption. In addition, the larger the number of a person's payment friends that were treated by the experiment, the more likely the individual is to adopt crypto. We find no evidence of diffusion of cryptocurrency adoption in the control group.[3]

Gambling Experiment: The second source of variation is a set of quasi-natural experiments in the adoption of gambling, when a set of 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, and at the end of our sample period, it remained illegal in the other states. We again first use this variation to confirm that peer networks matter for gambling adoption. We show this effect with two different approaches. First, in a quasi "first stage" analysis, we conduct a difference-in-differences estimation to document that the legalization of online gambling within a state results in larger gambling

1. Users on PayPal can send money to each other or share bills on the platform. We define payment friends only as those connections where both peers have sent money to each other so that the relationship is symmetric.

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

3. This may be a power issue since the control group was of limited size.

volumes and more gambling adoption of people living in these states relative to states where gambling was never legalized.[4] In addition, we find that the more payment friends that a user has, who are already gambling, the larger the treatment effect of gambling legalization. While this result is suggestive about the role of networks, it is not well identified since the number of gambling friends might be correlated with other characteristics of the user.

To address this endogeneity concern, we consider a sample of people who live in states where gambling is already legal (to ensure that they can legally react to a peer effect). We then identify gambling shocks to their peer network, such as having a payment friend who lives in a state where gambling just became legal. In the spirit of an intent to treat analysis, we use the variation from the legalization of gambling in the state that a friend lives in, not the endogenous adoption of gambling by a friend. We find 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. This setup allows for particularly convincing identification, since the peer's gambling exposure is exogenously shocked.

Equipped with these two experiments, we can then study directly whether peer networks compete for attention and time, implying that a given peer has a limited attention or time budget. In our context, we consider the social networks that are relevant for the adoption of crypto and gambling to be separate (though partially overlapping). Our data shows that only 9.2 percent of a person's crypto friends are also gamblers on average and vice versa, only 7.8 percent of a person's gambling friends are also PayPal Crypto users. This allows us to directly study whether these two networks compete for a person's attention. In particular, we look at whether friends that gamble detract from the use of cryptocurrencies and vice versa.

We find evidence for this hypothesis. Using first the crypto incentive experiment, we show that the treatment effect of the incentive campaign we reported above is significantly muted if the user had more gambling friends. In fact, we even find that the treatment effect of the crypto campaign seems to be diverted to other cryptocurrency platforms if the user has friends who have adopted crypto on other platforms, not PayPal. We can measure this diversion since we can see on the PayPal payment platform if users send money to other cryptocurrency platforms. But these heterogeneous treatment effects are only suggestive, since having gambling friends can be correlated with other omitted dimensions.

However, we can go a step further: In the "first stage" we showed that there is a strong positive treatment effect on a user in the treatment group if one of her network friends was also shocked by the crypto incentive campaign. However, in the spirit of peers competing for

4. We separately confirm the results using always legalized states as an alternative control group. We also conduct the analysis using the methodology by Callaway and Sant'Anna (2021).

the friend's limited attention, we see that this effect reverses if the treated friend happens to be a gambler himself. 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 particularly strong in the treatment group, and its magnitude is as large as the direct treatment effect from a friend being treated with crypto incentives (but with a negative sign).

Similarly, when looking at the opposite direction, using the quasi-exogenous variation from gambling legalization, we find that individuals whose states start allowing gambling, reduce their crypto trading. One might worry that this effect could still be driven by the endogenous composition of a person's network. Therefore, we also look at exogenous shocks to the gambling activities in a person 's peer network: people show a significant reduction in their trading volume in cryptocurrencies, in response to having a friend in a state being randomly shocked by gambling legalization. We also show that this crowd-out effect from gambling to crypto is even larger when the person has other gambling friends.

Again, these results confirm that peers with diverging interests compete for the attention and time of their network friends. We establish that peers with competing activities within a peer network can crowd out the adoption of new technologies or activities depending on where most interests within a given peer network lie. Our results also suggest that whenever researchers observe only one outcome or dimension of a peer network, they might capture only the net result across different (competing) peer effects. The results might have been much more heterogeneous if the researcher has been above to observe the offsetting peer activities.

Finally, we want to understand how narrowly (or broadly) peer effects in cryptocurrencies and gambling affect other spending categories on PayPal. For this purpose, we look at the total transaction volume (or total retail volume) of a user on PayPal. We do not find that peer-induced crypto (or gambling) adoption has a significant crowd-out effect on other spending on PayPal. This might suggest that users set a specific (attention) budget for risk-taking activities such as gambling or cryptocurrency trading, but do not let these activities spill over to unrelated activities. Of course, it is important to note that we do not have a measure of total consumption of the user, but we do capture a significant set of transactions for the users. In our sample, typical users who have engaged in gambling or purchased cryptocurrency on PayPal's platform spend approximately 8.6 percent of their income via PayPal.

1.1 Related Literature

There is a very large literature on the role of social networks in economics. Reviewing that literature is beyond the scope of this paper, 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 economic interactions and settings. 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 (defined mathematically using graph theory from the underlying network and includes measures such as the degree and centrality), and where in the structure an individual is.

More specifically, for example, there is a large literature studying how social networks, in particular, affect the adoption of various types of technologies, and a full review is again beyond the scope of this paper. A good review of the literature on the impacts of social networks on technology adoption in agriculture can be found in Suri and Udry (2022). Similarly, a good review of the role of peer groups and social networks in schools and hence in determining educational outcomes can be found in Paloyo (2020). There is now a growing literature on social networks and their impacts on fragility (Elliott and Golub (2022)), and migration (Munshi (2020)). There is also a large literature on social learning, which is rather distinct from what we measure here and focused on whether peers learn from each other in a variety of contexts (Mobius and Rosenblat (2014)). In this paper, we step aside from the social learning aspect and think more broadly about how peers influence each other, and whether different peer groups compete for this influence, without taking a stance on whether this is, in fact, (positive) learning or not. Finally, there is also a large literature on the role of social networks in finance more broadly (Kuchler and Stroebel (2021)).

Most of this literature uses survey data to define networks, collecting data on individuals' friends or friends by activity. Two exceptions are Houeix (2024) and Crouzet, Gupta, and Mezzanotti (2023) who use administrative data. Houeix (2024) studies the adoption of digital payments in the whole of Senegal using administrative data on all mobile money and digital payments accounts. He finds strong evidence that social networks matter for the adoption of digital payments, especially across sectors and space. Crouzet, Gupta, and Mezzanotti (2023) use administrative data from one payment wallet in India to study the role of demonetization in the adoption of digital payments. They find that social learning is less important in this context (though they do not have data directly on networks), and instead network externalities play an important role in explaining the diffusion. In this paper, we use data on networks that we build from actual PayPal transaction data (similar to Houeix (2024)), as we know who is transacting with who on the network.

Measuring social networks by asking about friends necessarily results in limited lists and, likely, lists that are "top of mind" at the time of the survey and our data seems to show that, indeed, the peers that influence you are likely to be subsets of all peers at any given time. These may or may not be the most important friends for financial or economic outcomes. If there is indeed limited attention, survey responses may just elicit the friends that are currently holding an individual's attention.

Of course, there is an equally large literature on attention constraints in behavioral economics, such as limited attention (Caplin (2016)), bounded rationality (Dhami and Sunstein (2022)), preferences for simplicity (Puri (2024)) and a large literature on behavioral finance (Hirshleifer (2015)). However, this literature focuses predominantly on an individual's attention constraints and the effects on efficient decision making. In this paper, we instead study whether an individual has a limited attention budget for their peers across different activities.

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2 Context and Data

2.1 Relevant Context on Crypto and Gambling

We now discuss the relevant context of cryptocurrency trading and gambling payments on PayPal. We also describe how we measure the peer networks for financial transactions. Our sample period covers several relevant changes in both the crypto and gambling environments.

Cryptocurrency Trading on PayPal: In October 2020, just prior to a steep rise in cryptocurrency prices, PayPal enabled its users to trade and invest in cryptocurrencies, with the token choices including Bitcoin, Ethereum, Litecoin, and Bitcoin Cash. Among these tokens, on the PayPal platform, 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 own tokens and hold them in a personal wallet on the relevant blockchain (this is the equivalent of a bank account in crypto parlance). But instead PayPal buys, holds, and sells these tokens on the users' behalf. By the end of April 2021, other crypto trading platforms also enabled new functionalities to allow their customers to link their crypto accounts to the customer's PayPal accounts so that the customer could use PayPal as the means of payment when transferring money to several cryptocurrency platforms. These other crypto platforms (OCP) show up as merchants in our data. During our sample period, there were $1.56 billion worth of total crypto transactions on PayPal and $1.16 billion of transactions that were facilitated through PayPal, but transferred to other cryptocurrency platforms outside of PayPal. We can trace retail transactions that are initiated from an individual's PayPal account and

send money to a cryptocurrency platform (merchant on the PayPal network). Finally, by October 21, 2020, PayPal had also launched its own digital coin. This was towards the end of our sample period, so we do not study this directly in this paper.

Gambling Deregulation: Over the past decade, the regulatory environment around online gambling has changed dramatically in the US. Gambling is regulated at the state level– individuals have to be physically present in gambling-legal states to be able to legally place bets. Over the past decade, online gambling and sports betting have become increasingly legalized. Nevada was the first state to legalize online sports betting in 2010, but successively other states followed. As of 2025, online gambling is legal in twenty-two states, thirteen of which changed their regulations during our sample period. Gambling was legal in Nevada, Delaware, New Jersey, West Virginia, Pennsylvania, Iowa, Rhode Island, Indiana and New Hampshire before our sample period. It became legal in Colorado, Illinois, Tennessee, Virginia, Michigan, Wyoming, Arizona, New York, Louisiana, Kansas, Maryland, Ohio and Massachusetts during our sample period (though Ohio and Massachusetts only in 2023). In the analysis, of these thirteen, we drop Colorado, Illinois, and Tennessee, as they legalized gambling too close to when PayPal enabled its crypto platform. We provide a table with the exact dates when gambling became legal in different states in Table B2.

Online gambling sites restrict access to people in gambling-illegal states by identifying and regulating IP addresses. Individuals should be able to access online gambling sites and place bets only when 1) they live in a gambling-legal state, or 2) they live in a gambling-illegal state but travel to a state where online gambling is legal. Whilst our primary focus is on the former case, we also study the latter case and consider the states to which users travel most. Nonetheless, there is always the potential concern that some people will try to gain access via illegal means, such as using fake IP addresses or VPNs. Common advertisement platforms such as Google also abide by state laws in that they do not display gambling-related advertisements to people in gambling-illegal states.

The legalization of online gambling in U.S. states has several key features that are useful for our analysis. First, given the regulation changes described above, we have a set of natural experiments to study gambling behavior. Second, there is very limited contamination of the "control group" in this case, as both online gambling sites and advertisement platforms abide by state laws and restrict exposure to people in gambling-illegal states.

2.2 Core Data

Our data comes entirely from PayPal, one of the largest global payment processing firms. Compared to some of its competitors, such as Visa or Mastercard, PayPal also has information on the merchants and customers who are engaging in the transactions. For example,

PayPal had 432 million active global accounts as of 2023. In contrast, Zelle serves around 120 million consumer and small-business accounts, while Cash App has approximately 44 million active users. We have access to de-identified (encrypted) data from PayPal on its customers, at the transaction level, from 1st January 2020 through 1st April 2023. We focus only on US customers in this data. This covers 133 million total (unique) users over this period who made a total of 234 million person-to-person (P2P) payments, 3.8 billion retail purchases, and 7.2 million crypto purchases on PayPal. Appendix Table B1 provides a detailed description of all the variables used in our analyses.

For each transaction, we have data on 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 a measure of social networks on PayPal. In particular, we can identify a person's close peers, which we call symmetric friends on PayPal: These are users who have sent payments to and received payments from each other (this is the same measure of a social network as that used by Houeix (2024)). For our core analysis, we will use the number of symmetric payment friends on PayPal that a given user has as a measure of the user's overall social 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 transactions on the PayPal network that appear to be hidden one-directional payments.

For each user, we also observe some of their demographics,[5] in particular their age, a measure of their income, their state of residence, how actively they engage on the platform, and their digital transaction attributes (flags PayPal users to categorize their customers 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

5. 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 internal estimates generated from transaction data and Acxiom data.

(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 0.128. 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, 37 transactions a year, though the 90th percentile of this variable is closer to 400. Of these transactions, on average, 3 are P2P and 23 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 addition to individual users, from the transaction data, we are able to identify and classify 4.1 million merchant accounts, where we can observe their business name, their state of operation, their business type and their size [6] (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 PayPal codes the types of merchants in their data.). We can then trace PayPal user transactions to this merchant. There are 855 thousand unique online gamblers on PayPal, with 17 million gambling transactions during our sample period.

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, gamblers are the highest,

6. This is a variable created by PayPal.

followed by crypto users. 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 less likely to be high-income than cryptocurrency users.

3 Empirical Framework

As mentioned above, our empirical analysis uses two main sources of identifying variation. The first is a set of marketing incentive experiments (randomized) that PayPal ran on their network. The second is quasi-experimental variation around the legalization of gambling across some US states. We discuss each of these separately below for our basic results that we use to first document that peers do indeed matter, on average, for the adoption of financial instruments like the use of crypto and gambling. We then discuss the analysis we conduct to look at peer competition for attention. Note that Appendix Table B1 provides a description of all the variables used in our analyses.

3.1 Marketing Incentive Experiments in Crypto

Once PayPal allowed the use of crypto on their platform, they ran several marketing incentives experiments (randomized A/B tests) to encourage the use of crypto on the platform. To understand the role of social networks, we leverage the variation provided by these experiments. These experiments were not conducted on the entire PayPal user base, so for this analysis we restrict the sample to the set of users that were part of these experiments (either as treatment or control).

In particular, we focus on one set of marketing incentive campaigns run by PayPal. This was run in the first quarter of 2022 from February 15th through April 12th. This campaign covered 34 million total users on the PayPal platform, with 339,000 allocated to the control group and the rest to the treatment group. This campaign offered $5 worth of crypto as a reward to users who set up their PayPal crypto wallet to buy crypto.

There was a second campaign was in the second quarter of 2022, from 22nd April through to 23rd June. This included 12 millions users in the treatment group and 603,000 users in the control group. The incentive in this campaign was much larger, with a $25 crypto reward to users who bought at least $100 worth of crypto in a single purchase. Much as the incentive was much larger, many fewer users were treated and also later when crypto was already being used. We do not focus on this experiment but we do report results from it in the Appendix. There are no explicitly defined "termination dates" to the experiments, we consider such dates as the time when another crypto-related experiment is launched, to prevent any contamination resulting from overlapped treatments.

In Table 1B (the second panel), we compare how the main experimental sample we use compares to the overall user base of PayPal. The experimental sample is more interactive on PayPal. They have slightly more friends, but they conduct a lot more total transactions as well as P2P transactions (almost double compared to the average PayPal user). However, they are not different 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.

Using the first experiment, we run two sets of analyses. First, we test whether the marketing incentive campaign had any effects on the adoption of crypto by running the following regression:

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

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 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.

In Table 1B (the third panel), we compare the experimental sample to the sample that has symmetric friends as per this definition. 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.

Second, we study the peer diffusion of crypto using the experimental variation from these same marketing incentive experiment using the following regression specification:

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

where, in addition to the variables defined in equation (1), *Sym Treated* is defined as the number of the users' payment friends who received the crypto incentive treatment for the 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 into the control group. In these specifications, the random variation comes from the number of treated friends being random conditional on the total number of friends. So we also control for the total number of friends in these specifications (i.e . *Sym Degree*).

We also use a similar specification to look at the interactions of cryptocurrency adoption on PayPal with other cryptocurrency platforms (OCP). In particular, we want to understand if the marketing experiments conducted by PayPal had a spillover effect on OCP and whether these spillover effects are amplified if someone had existing peers that were already using OCP. For that, we estimate the following specification on the same experimental sample:

$$\begin{aligned} Y_i = \alpha + \beta Treated_i + \gamma_1 SymDegree_i + \gamma_2 SymCrypto_i + \delta_1 OCP_i \\ + \delta_2 SymOCP_i + \eta_1 OCP * Treated + \eta_2 SymOCP * Treated \\ + \psi Transactions_i + \epsilon_i \end{aligned} \tag{3}$$

where *OCP* is an indicator variable for whether the user had purchased crypto from OCP before the incentive experiment; *Sym OCP* is the number of the users' friends who had purchased on OCP before the experiment. We are specifically interested in the interactions of these two variables with the treatment indicator for the marketing incentive experiments, i.e. in the coefficients η_1 and η_2. In terms of outcomes, we look at both the purchase of crypto (as we were in the two earlier specifications) as well as whether the person uses OCP within the first two months after the incentive experiment.

3.2 Natural Experiment: Legalization of Gambling

Using the natural experiment for gambling described above, we conduct a similar analysis for gambling. We first study whether the legalization of online gambling in the relevant states led to more gambling and how this effect diffuses through the relevant peer group of gambling friends.

For the gambling analysis, we use a natural experiment where a set of US states legalized online gambling over our sample period. To conduct this analysis, we create a panel dataset from the PayPal transaction data at the individual-month-level spanning November 2020

through April 2023. Although the data is available prior to November 2020, we chose this period since PayPal launched its crypto platform on October 21, 2020. Since we can only capture cryptocurrency purchases after that date, and the core of our peer analysis looks at interactions between crypto purchases and gambling behavior, this restriction allows us to be consistent across all our analyses. In addition, we restrict the sample to users who created their PayPal accounts before November 1, 2020, so as to ensure full visibility of their transaction activities throughout the sample period. This sample includes a total of 58.9 million PayPal users.

In Table 1A, we show summary statistics for this sample of PayPal users, what we call the gambling sample. In the table, we compare the demographic characteristics of PayPal 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.

The substantive difference between the gambling analysis and the crypto analysis is that the identifying variation we use here is a natural experiment given several states legalized online gambling over our sample period. At the core, we therefore use a standard generalized difference-in-differences (DiD) framework to analyze the gambling regulation changes. We exclude states that legalized gambling before our sample period. Our control group in any given month is made up of two groups: (i) the states that never legalized gambling, and (ii) states that legalized gambling over our sample period, but after the month in question.

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

$$Y_{it} = \beta Legalized_{it} + \mu_i + \gamma_t + \epsilon_{it} \tag{4}$$

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*).

We also look at the impact that the legalization of online gambling in an individual's friends' states has on their gambling activity. In particular, we look at the peer effect of gambling legalization on individuals residing in states where online gambling has always been legal, but who had never gambled before the first legalization during our sample period. For this specification, we select users who registered their residency in states where online gambling was permitted prior to 2020, but who had not engaged in gambling until the legalization of online gambling in Virginia on January 21, 2021 (the first legalization in our sample period after PayPal enabled their crypto platform). This sample includes 7.74 million PayPal users. For this sample we run the following specification:

$$Y_{it} = \beta SymLegalized_{it} + \sigma SymLegalized_{it} * SymGamble_i + \mu_i + \gamma_t + \epsilon_{it} \tag{5}$$

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; *Sym Gamble* is the number of the user's friends who gambled during the sample time period but prior to the user's own start to gamble. Note that one of the main effects for this interaction is subsumed in the two way fixed effects in this specification. In terms of outcomes, for this specification, we report results only for *Gamble Vol* and *Gamble Share*).

4 Results

4.1 Peer Effects in Cryptocurrency Adoption

In Table 3, we first confirm that the marketing incentive campaigns had an impact on the use of cryptocurrencies 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; and Column (7) through (9) restrict the sample to those who are in the gambling natural experiment. We define the attentive uses to be those who opened the email PayPal sent them regarding the marketing incentive campaign. Note that the coefficients in this table have been multiplied by 1000 for readability.

As this table shows, the incentive experiments had large and significant impacts on the adoption of cryptocurrency, when compared to the mean in the control group (which is reported at the bottom of the table). In Column (1), we estimate a basic regression to

establish the treatment effect. The effect of the incentives is to increase the adoption of crypto in the two months following the experiment by almost 60%.

In Column (2), we add controls for $SymCrypto$, $SymDegree$, and $LogNumTxn$to examine how network connectivity and past transaction behavior influence adoption. In Column (3), we further decompose $SymCrypto$ to differentiate between having exactly one crypto friend and having more than one, allowing us to assess the non-linearity of network effects. Examining $SymCrypto$ in Column (2), we find that having one additional crypto-using friend before the experiment is associated with a 0.14 percentage point increase in the probability of adopting crypto. This effect is substantial—approximately three times the magnitude of the direct treatment effect. In Column (3), we observe that having more than one crypto friend ($SymCrypto > 1$) is associated with an even larger 0.4 percentage point increase in adoption probability. This pattern aligns with the expectation that larger crypto networks amplify adoption effects.

Adding a variety of controls, such as age, income or the state a person lives in, do not affect the results. Also note that the coefficients on the variables describing symmetric friends are not causal in these specifications so we do not discuss these coefficients here.

These relationships hold across different subsamples. In the sample of attentive users, i.e. those that enter their emails from PayPal, the adoption of crypto in the control is higher, and the effect of the incentives is also slightly larger - in this sample the incentives increase the probability a user purchases crypto by almost 70%. When we restrict the sample to those in the gambling natural experiment, we see slightly larger effects, close to 100% increases in the probability of adoption crypto. The aim of looking at this sample is to simply show that the incentive campaign did have effects on that subsample of PayPal users as well, since our later analysis using the gambling experiment will focus on that sample. Appendix Table 3 shows a similar set of results for the second experiment.

In the Attentive Users group, the estimated coefficient for $SymCrypto > 1$ suggests that having multiple crypto friends is associated with a 1.3 percentage point increase in the likelihood of adoption. This result highlights the particularly strong role of network effects in the subset of users who engaged with the incentive campaign.

4.2 Amplification through Treated Peers

In Table 4, we now look at the diffusion of crypto among peers using the specification in equation (2) above. As described above we run these specifications separately by treatment and control group, as there is no reason to assume that diffusion would be the same 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 a compounding effect. 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 60% increase in the probability of adoption from the treatment. The difference between the treatment and control group suggests that a treated friend

In Columns (3) and (4), we introduce *SymCrypto* as a control to assess the peer effect of having pre-existing crypto-using friends. We find that in the treatment group, each additional crypto-using friend before the experiment is associated with a 0.15 percentage point increase in the probability of adopting crypto. However, in the control group, the effect is close to zero and statistically insignificant. Even after accounting for the sample size difference between treatment and control groups, the magnitude of the effect remains substantially larger for treated users, reinforcing the idea that the incentive campaign amplifies the impact of social networks on adoption. This suggests that crypto adoption spreads more effectively within an incentivized environment, where users are more responsive to peer influence.

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 important diffusion and compounding 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 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

influence 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 examines 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. Given these mixed findings, further research may be needed to explore the mechanisms driving these differences.

4.3 Spillovers to Other Crypto Platforms

In Table 5, we study whether an individual's use of other crypto platforms affects their response to the treatment as well as whether there is diffusion of crypto through other crypto platforms. Users on PayPal can buy cryptocurrencies directly on their platform, but we can also observe when they send money to other cryptocurrency platforms via PayPal. We cannot observe of course what types of trading activities people conduct on these alternative platforms. But we take the act of sending money to identified cryptocurrency platforms, as a sign of crypto adoption on the other platform. Columns (1) through (3) look at the adoption of crypto on PayPal, and Columns (4) through (6) the adoption of other crypto platforms. In Column (7), we look at whether a user took up using other crypto platforms only but did not purchase any PayPal crypto.

Column (1) shows the impact of the incentive campaign and how that varies for those who already used other crypto platforms. We do not see any statistically significant differential impacts, though the magnitudes are large (especially given the magnitude of the treatment effects themselves). In Column (2) we look at whether the treatment effects are amplified by having friends on other crypto platforms - here again, we do not find statistically significant effects, and with smaller magnitudes than in Column (1). In Column (3), we look at whether the use of other crypto platforms affects the diffusion of crypto through crypto friends - here, we find negative effects (though again no statistically significant, and not large in magnitude).

In Columns (4) through (6) we look at similar specifications, but this time with the adoption of other crypto platforms as the outcome. We do find that the incentive campaign has effects on the adoption of other crypto platforms, but we do not find much evidence of diffusion through other crypto platforms. The treatment effects on other crypto platforms are about a quarter the size of the treatment effects on crypto itself. In Column (7), we find similar results than we find in Column (5), suggesting the limited overlapping effects of PayPal and other crypto platforms.

Comparing Columns (1) through (3) with Columns (4) through (6), we observe that having a stronger network within PayPal is associated with a higher probability of adopting crypto on PayPal than on other platforms. Specifically, the coefficient on $SymDegree$, which captures overall network connectivity, is positive and statistically significant for PayPal crypto adoption but insignificant for other crypto platforms. This suggests that a user's engagement within the PayPal ecosystem plays a crucial role in shaping their adoption decision.

Similarly, the coefficient on $SymCrypto$, which measures the number of pre-existing crypto-using friends, is approximately five times larger for PayPal crypto adoption than for adoption on other crypto platforms. This substantial difference highlights the importance of within-platform peer effects in driving crypto adoption.

Conversely, having more friends on other crypto platforms is associated with a higher likelihood of adopting crypto on those platforms instead of PayPal, as seen in the positive and significant coefficient on Sym OCP in Columns (4). This result is consistent with the idea of network effects, where users are more likely to follow adoption patterns within their existing peer groups rather than switch to a new platform.

4.4 Impact of the Legalization of Gambling

In Table 6, we look directly at the natural experiment on gambling. We use the DiD framework described above to look at the impact of the legalization of online gambling in the individuals' states on their online gambling volumes. Columns (1) and (2) examine the user's online gambling volumes for the full sample as defined above; Columns (3) and (4) look at the effects of legalizing gambling on the same two outcomes, but for the sample of users that were part of the marketing incentive campaign. And finally, the last two columns restrict the sample to states where experienced the online gamble legalization shocks.

Overall, we find large effects of the legalization of online gambling in a state. For any given PayPal user (in the full sample) which is presented in Column (1), the legalization of online gambling raises gambling volumes by \$1.43, which in terms of an effect size is about a 165% increase in gambling expenditures (the mean is low because a large share of

PayPal users do not gamble). Column (2) further shows the effects on the share of total transactions attributed to gambling increased by 0.36 percent points, which, while seemingly small, represents a meaningful shift in consumer spending patterns.

A similar trend is observed when we restrict the sample to users who were part of the PayPal crypto marketing incentive campaign (Column (3) and (4)). Here, we find a slightly smaller but still significant increase of $1.35 in gambling volume. The effects remain stable when we analyze only the sample of users in states that legalized gambling during the period (Column (5) and (6)), where the estimated effect is slightly larget at $1.5691. These consistent results suggest that the online legalization shock is robust across samples.

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 later examine how this shock spills over through social networks. Specifically, if gambling legalization increases gambling activity among treated users, it may also lead to increased engagement among their connected peers, reinforcing the role of network diffusion.

4.5 Peer Effects and the Legalization of Gambling

In Table 7, we look at the amplification of gambling through peer groups. Specifically, we investigate whether individuals are more likely to increase their gambling activity when they have more peers who gamble prior to the legalization shock. The peer groups analyzed here consist of friends who had engaged in gambling transactions prior to the user, allowing us to measure the network effects of pre-existing gambling behaviors.

In Columns (1) through (4), we look at the full sample and in Columns (5) through (8) we restrict the sample to the marketing incentive experiment sample. For each sample, we show the same two outcomes as in Table 6: gambling volume and the share of gambling in total transactions. In addition, we look at how the effects of legalization vary with the number of gambling friends by looking separately at the heterogeneity by the total number of friends, as well as splitting this out by whether a user had one gambling friend or more than one (as we did for the diffusion of crypto above).

As the table highlights, peer effects significantly amplify the impact of gambling legalization. First, the direct effect of *Legalized* is large and highly significant across all specifications, confirming that legalization substantially increases individual gambling activity. In Column (1), users in states that legalized online gambling increase their monthly gambling volume by $ 1.37. Column (2) shows that the share of total transactions attributed to gambling rises by 0.33 percentage points. Similar patterns emerge in the marketing incentive sample (Column (5) and (6)), where gambling volume increases by $1.26 and gambling share increases by 0.35 percentage points. These effects are consistent across subsamples,

reinforcing the robustness of the legalization shock.

In addition to the direct effects, we observe strong and highly significant peer effects. The coefficient on $LegalizedXSymGamble$ suggests that having more gambling-connected friends amplifies the effect of legalization on gambling spending. In Column (1), the full sample, each additional gambling friend increases monthly gambling volume by \$7.71 following legalization. A similar but slightly smaller effect is found in the marketing incentive sample in Column (5), where each additional gambling friend increaes gambling volume by \$ 6.49. These results indicate that gambling behavior is not only influenced by individual exposure to legalization but also propagates through social networks.

When we further differentiate between users with exactly one gambling friend versus those with multiple gambling friends, we find strong evidence of an amplifying effect. The corfficient on $LegalizedXSymGamble = 1$ indicates that having one gambling friend increases gambling volume by \$8.07 in the full sample. However, for users with more than one gambling friend, the coefficient on $LegalizedXSymGamble > 1$ is nearly twice as large, at \$19.2. This pattern holds in the marketing incentive sample. These findings confirm that having multiple gambling friends dramatically magnifies the impact of legalization on individual gambling behavior.

Taken together, the results in Table 7 show that gambling legalization not only has a direct impact on individual behavior but also diffuses strongly through peer networks. The more gambling-connected friends a user has, the greater their response to the legalization shock. These findings parallel the patterns observed in crypto adoption, where network effects played a crucial role in driving behavior changes. This evidence reinforces the idea that policy changes affecting financial behaviors do not operate in isolation but propagate through social networks, shaping financial decision-making on a broader scale. These insights will be particularly relevant for subsequent analyses that explore the diffusion of financial behaviors beyond gambling transactions.

4.6 Peer Shocks from the Legalization of Gambling

In Table 8 we now analyze the impact on a person's gambling activities if they have a friend who lives in a state where gambling becomes legalized. 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. And we can then study whether the random shock to the friend is submitted to the peer network. Compared to the analysis of heterogeneous treatment effects in the prior section, we do not rely on the endogenous composition of the gambling or crypto interests of a person's peers. But we hold the peer network fixed and look at shocks to the peer's interests. For this analysis we include the sample of people who

live in states where did not change gamble legalization statues, but who did not gamble themselves.

The results in Table 8, Column (1) shows that there is a very strong positive effect on a person, when a friend in another state is exposed to gambling being legalized. The control group are people in the sames 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. In Column (3) we repeat this analysis but only look at shocks from friends who themselves adopted gambling after their state legalized gambling. We can see in Column (3) that the effect is almost four times as large as the ITT results. This analysis focuses on the people who choose to endogenously adopt gambling in response to the legalization. Thus it is not surprising that the results are much stronger, but it is reassuring that the mechanism is works through the friends themselves adopting gambling. The results are very similar in Column (5) when we include both the dummy for whether a friend's state legalized gambling, and whether the friend adopted gambling.

Finally in Columns (7) and (8) we also look at the heterogeneous treatment effect, if the user had other friends who are gamblers. The treatment effect estimated in Column (1) is significantly increased if the user has other gambling friends, in addition to having a friend living in a state where gambling was just legalized. In Column (8) we also include the interaction with the number of friends who are cryptocurrency users and find no significant amplification effect.

5 Competing for Peer Attention

Equipped with the peer experiments described above, we are now ready to analyze whether competing interests of peers within a network crowd out the adoption of other behaviors or 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 network. In our context, given the incomplete overlap in payment friends and gambling friends, we can ask whether gambling friends add to or detract from crypto adoption. Similarly, we can ask whether crypto friends add to or detract from gambling adoption.

5.1 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 add the treated gambling friends to the crypto specifications.

$$
\begin{aligned}
Y_i = \ & \beta SymTreated_i + \eta Gambled_i + \sigma SymGamble_i \\
& + \rho SymGambleTreated_i + \delta X_i + \epsilon_i
\end{aligned}
\tag{6}
$$

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 also received the crypto marketing incentive treatment described above.

In Table 9, we document the results from this analysis. Columns (1), (3), and (5) analyze the treatment group, while Columns (2), (4), and (6) analyze the control group, using the full experimental sample. Columns (1) and (3) show that having a friend who is both a gambler and treated by the experiment ($SymGambleTreated$) reduces an individual's probability of adopting PayPal Crypto by 0.05 percentage points. The magnitude of this effect is as large as the direct effect from the incentive campaign, but it goes in the opposite direction and therefore undoes the effect of an average peer being treated by the incentive campaign. Interestingly, we find that the direct effect of an individual having engaged in gambling before the experiment ($WasGamble$) is positive. This result might suggest that people who have a propensity to gamble are also more willing to try out cryptocurrencies. But notably, the effect of a friend who is a gambler being treated goes in the other direction. I.e. friends who are gamblers reduce the likelihood of their friend to engage in crypto trading.

In Columns (5) and (6) of Table 9, we introduce a control for the total number of gambling-connected friends ($SymGamble$). The results indicate that having more gambling friends further decreases the probability of adopting crypto. Moreover, the previously observed effect of treated gambling friends disappears, suggesting that the overall influence of gambling networks, rather than specific treated peers, explains the reduction of crypto adoption. For the control group, Column (6), there is no significant relationship between gambling-related variables and crypto adoption; the estimated coefficient are much smaller and insignificant across the board. Since individuals in the control group are not incentivized to adopt crypto trading, the baseline adoption is much smaller which might make it harder for us to find effects.

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. This reinforces the idea that diverging peer influence in the adoption of new activities or products can crowd out or inhibit adoption, depending on the network

composition.

5.2 Peer Competition from Gambling on Crypto Trading

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.

$$\begin{aligned} CryptoVolume_{it} = \beta Legalized_{it} + \sigma_1 Legalized_{it} * SymGamble_i \\ +\mu_i + \gamma_t + \epsilon_{it} \end{aligned} \tag{7}$$

Table 10 shows the results from this analysis. The first four columns include the full sample of people affected by the gambling legalization, including the large fraction of people who do not trade cryptocurrencies. And the later four columns condition only on people who were crypto traders prior to the beginning of the legalization. Column (1) documents the basic difference in differences analysis of monthly crypto volume as a function of the gambling legalization dummy and an interaction term of legalization with the number of symmetric gambling friends. The direct effect of the legalization is strongly negative; crypto trading decreases by almost 25% after the legalization of gambling compared to non-legalizing states. This result holds independent of peer effects, but suggests that these two activities are not complements but substitutes in people's budgets. In addition, we see that the negative effect on crypto trading is particularly strong for people who have symmetric gambling friends.

In Column (2) 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, and the effect doubles for people with more than one friend. In Columns (3) and (4), we repeat the same analysis but use as a dependent variable the crypto share, i.e. the fraction of a person's budget that is spent on cryptocurrencies. The results confirm the ones in Columns (1) and (2). Finally, in Columns (5)-(8) we repeat the same analysis but condition only on PayPal users who are crypto traders. Not surprisingly the estimated coefficients are much larger, since we do not include the large fraction of people who never trade cryptocurrencies. But qualitatively the results are very similar to before.

Overall, Table 10 suggests that increased access to gambling activities crowds out crypto trading on average. But this crowd out effect is vastly 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. However,

one might still worry that the network effect in this analysis is not perfectly identified, since having more peers with gambling interests could be endogenous to the person's own propensity to be interested in gambling.

Here our second identification strategy allows us to use shocks to the peer's exposure to gambling as explained above. In Table 11, we look at the impact of the legalization of gambling in a friends' state on the person's crypto purchasing behavior. Does gambling legalization among peers diverts financial engagement away from crypto purchases, suggesting competition for peer attention? As before the sample is restricted to users who reside in states that did not experience a gambling legalization shock and who had not engaged in gambling prior to the first legalization shock. This ensures that any observed effects are driven by peer exposure to gambling legalization rather than direct personal exposure.

The results indicate that peer gambling legalization leads to a significant decline in crypto purchases, suggesting a competition for financial attention between gambling and crypto transactions. The coefficient on $SymLegalized$ is negative and highly significant, with Column (1) showing that gambling legalization in a friend's state reduces monthly crypto purchases by \$1.38. This effect remains similar in Columns (3)–(4). In addition, the negative and significant coefficient on $SymLegalizedXSymGamble$ in Column (4) (\$-1.18) 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.

5.3 Peer Competition and Crowd Out of Other Transactions

Finally, we want to understand if the crowd effects from the shock to gambling legalization is contained to crypto trading or if we see crowding out of other activities as well. We can look at this directly in the PayPal data as we can look at other expenditures on the platform and see if this is negatively affected by gambling and/or crypto friends. Of course, we only have administrative data from PayPal, which is a bit less than ten percent of a user's annual income, and not full consumption data for the users in the sample. In particular, we run the following specification:

$$\begin{aligned} TotalRetailTransactionVol_{it} = \beta Legalized_{it} + \sigma_1 Legalized_{it} * SymGamble_i \\ + \sigma_2 Legalized_{it} * SymCrypto_i + \mu_i + \gamma_t + \epsilon_{it} \end{aligned} \tag{8}$$

We show in Table 12 that there is only minimal spill over from gambling legalization on other retail spending of treated customers. We do not find that peer-induced gambling adoption has a significant crowd-out effect on other spending on PayPal. This might suggest

that users set a specific (attention) budget for risk-taking activities such as gambling or cryptocurrency trading, but do not let these activities spill over to unrelated activities. Of course, it is important to note that we do not have a measure of total consumption of the user, but we do capture a significant set of transactions for the users. In our sample, typical users who have engaged in gambling or purchased cryptocurrency on PayPal's platform spend approximately 8.6 percent of their income via PayPal.

6 Conclusion

Using data from the PayPal platform that provides us with payment transactions of more than 70 million users, we document a new crowding-out mechanism within peer networks. A large literature has shown the positive impact of peers in the transmission and diffusion of information and the adoption of new behaviors. But most of these papers study one activity within a network at a time. We show that there can be impeding (crowding out) effects on the adoption of particular activities, if participants within a network have diverging interests, and compete for the attention or time of their network members. We document in our context that there is a strong crowding out effect between cryptocurrency adoption and gambling, in either direction. [TBC]

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

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	25.26%	33.69M	31.67%	10.63M	18-29	24.02%	53.26M
30-49	41.17%	54.90M	42.90%	14.39M	29-49	39.2%	86.91M
50+	33.57%	44.77M	25.43%	8.53M	50-69	36.77%	81.52M
Total						100%	221.70M
Income							
Low (<50k)	42.92%	57.23M	41.73%	14.00M	<50k	41.5%	49.45M
Medium (50k-125k)	44.61%	59.50M	45.12%	15.14M	50k-100k	36.92%	43.99M
High (125k +)	12.47%	16.63M	13.15%	4.41M	100k +	21.59%	25.72M
Total	100.00%	133.36M	100.00%	33.56M		100%	119.17M
Top States							
CA	10.31%	13.75M	11.37%	3.81M	CA	11.78%	39.04M
TX	8.16%	10.88M	9.02%	3.03M	TX	9.06%	30.03M
FL	7.40%	9.88M	6.67%	2.24M	FL	6.71%	22.25M
NY	5.48%	7.30M	5.77%	1.94M	NY	5.94%	19.67M
PA	3.56%	4.75M	3.86%	1.30M	PA	3.91%	12.97M
IL	4.18%	5.57M	3.77%	1.26M	IL	3.80%	12.58M
Total	39.09%	52.13M	40.46%	13.58M		41.20%	136.54M

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

Table 1B: Summary Statistics, PayPal 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.

	Obs	Mean	P25	P50	P75	P95	P99
All Sample							
Symmetric Degree	133.36M	0.128	0	0	0	1	3
Number of Total Transactions Per Year	133.36M	37.4	0	4	34	183	391
Number of P2P Transactions Per Year	133.36M	2.75	0	0	1	13	48
Number of Retail Transactions Per Year	133.36M	22.8	1	5	25	101	206
Fraction of People Ever Gambled	133.36M	0.00997	0	0	0	0	0
Fraction of People Ever used Coinbase	133.36M	0.00779	0	0	0	0	0
Fraction of People Ever used Crypto	133.36M	0.0108	0	0	0	0	1
All PayPal Experiment Participants							
Symmetric Degree	33.56M	0.158	0	0	0	1	3
Number of Total Transactions Per Year	33.56M	55.9	5	19	66	229	452
Number of P2P Transactions Per Year	33.56M	5.18	0	0	3	24	74
Number of Retail Transactions Per Year	33.56M	25.4	2	8	29	106	214
Fraction of People Ever Gambled	33.56M	0.00986	0	0	0	0	0
Fraction of People Ever used Coinbase	33.56M	0.00775	0	0	0	0	0
Experiment Participants with Symmetric Friends							
Symmetric Degree	3.58M	1.48	1	1	2	3	6
Number of Total Transactions Per Year	3.58M	108	20	60	140	362	678
Number of P2P Transactions Per Year	3.58M	23.1	4	10	26	83	179
Number of Retail Transactions Per Year	3.58M	41.1	3	18	54	154	298
Symmetric Crypto	3.58M	0.0461	0	0	0	0	1
Symmetric Coinbase	3.58M	0.0233	0	0	0	0	1
Fraction of People Ever Gambled	3.58M	0.0232	0	0	0	0	1
Fraction of People Ever used Coinbase	3.58M	0.0115	0	0	0	0	1
Gamble Legalization Sample							
Symmetric Degree	73.62M	0.21	0	0	0	1	3
Number of Total Transactions Per Year	73.62M	59.8	3	20	74	244	470
Number of P2P Transactions Per Year	73.62M	3.91	0	0	2	19	59
Number of Retail Transactions Per Year	73.62M	28.3	2	9	35	116	225
Fraction of People Ever Gambled	73.62M	0.0168	0	0	0	0	1
Fraction of People Ever used Coinbase	73.62M	0.0124	0	0	0	0	1
Fraction of People Ever used Crypto	73.62M	0.0145	0	0	0	0	1

Note: In the top panel, we show summary statistics for the full sample.
In the second, panel we show summary statistics for the sub-sample of users involved in the experiment.
In the third panel, we show summary statistics for the experiment sample who have at least one friend.

Table 2. Gamblers and PayPal Crypto and Coinbase Users

This table reports summary statistics for three distinct user groups: PayPal crypto users, Coinbase 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, while Coinbase users are those who have made crypto purchases from Coinbase using 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 columns report standard deviations for each variable.

	Crypto N=1.19M		**Coinbase** N=678K		**Gamble** N=855K	
	Crypto Mean	Crypto SD	Coinbase Mean	Coinbase SD	Gamble Mean	Gamble SD
Symmetric Degree	0.3367	0.9028	0.2721	0.7928	0.4298	1.0858
Number of Total Transactions Per Year	99.6278	167.5926	119.2763	151.5428	136.926	166.1471
Total Transaction Volume Per Year	5,526.65	10,124.33	7,805.95	11,961.79	8,395.45	19,215.82
Number of P2P Transactions Per Year	10.8463	31.9668	8.3672	27.9672	10.3486	32.6117
P2P Transaction Volume Per Year	1,452.56	5,240.82	1,374.52	5,474.15	1,749.20	8,654.22
Number of Retail Transactions Per Year	45.842	79.168	53.6306	70.7715	61.4316	78.0266
Retail Transaction Volume Per Year	2,081.54	3,809.77	3,104.95	4,751.76	3,220.03	7,045.70
Age: 50+	0.239	0.4265	0.1603	0.3669	0.1888	0.3913
Age: 30-49	0.5267	0.4993	0.5068	0.5	0.5347	0.4988
Age: 18-29	0.2343	0.4235	0.3329	0.4713	0.2765	0.4473
Income: >$125K	0.1177	0.3223	0.1489	0.356	0.2084	0.4062
Income: $50-125K	0.432	0.4954	0.4744	0.4993	0.491	0.4999
Income: <$50K	0.4503	0.4975	0.3767	0.4845	0.3006	0.4585

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 44,000 users who were both gamblers and PayPal crypto users.
There were about 79,000 users who were both PayPal crypto users and Coinbase users.
There were about 40,000 users who were both gamblers and Coinbase users.
T-tests of differences in means between crypto and gambling users reject the null of no differences for all characteristics.
T-tests of differences in means between Coinbase and gambling users reject the null of no differences for all characteristics.

Table 3. Adoption of Crypto in Incentive Experiment

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. Columns (7)–(9) focus on users residing in states where legalized gambling during our sample period. 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			Gamble Legalization Users		
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Treated	0.452***	0.453***	0.453***	0.888***	0.888***	0.888***	0.424***	0.425***	0.425***
	(0.047)	(0.047)	(0.047)	(0.204)	(0.204)	(0.204)	(0.051)	(0.051)	(0.051)
Sym Crypto		1.366***			2.500***			1.226***	
		(0.066)			(0.295)			(0.068)	
Sym Crypto = 1			1.334***			2.089***			1.203***
			(0.070)			(0.314)			(0.072)
Sym Crypto >1			3.904***			13.072***			3.367***
			(0.413)			(1.760)			(0.414)
Sym Degree		0.256***	0.255***		0.352***	0.346***		0.237***	0.237***
		(0.008)	(0.008)		(0.038)	(0.038)		(0.008)	(0.008)
Log Num Txn		0.045***	0.045***		-0.030*	-0.030*		0.052***	0.052***
		(0.003)	(0.003)		(0.012)	(0.012)		(0.003)	(0.003)
Intercept	0.277***	0.661***	0.661***	0.438*	1.565***	1.566***	0.271***	0.572***	0.572***
	(0.047)	(0.058)	(0.058)	(0.203)	(0.252)	(0.252)	(0.051)	(0.063)	(0.063)
Control Mean	0.0003	0.0003	0.0003	0.0004	0.0004	0.0004	0.0003	0.0003	0.0003
Age	N	Y	Y	N	Y	Y	N	Y	Y
Income	N	Y	Y	N	Y	Y	N	Y	Y
State	N	Y	Y	N	Y	Y	N	Y	Y
R-Squared	0.00	0.0002	0.0002	0.00	0.0006	0.0006	0.00	0.0002	0.0002
Adj. R-Squared	0.00	0.0002	0.0002	0.00	0.0005	0.0005	0.00	0.0002	0.0002
Observations	33.56M	33.56M	33.56M	3.16M	3.16M	3.16M	26.97M	26.97M	26.97M

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

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	0.432***	0.0018	0.436***	-0.008			0.589***	0.143		
	(0.027)	(0.164)	(0.027)	(0.166)			(0.123)	(0.693)		
Sym Treated = 1					0.436***	-0.008			0.595***	0.148
					(0.027)	(0.166)			(0.123)	(0.693)
Sym Treated >1					0.231***	0.383			-0.440	-0.488
					(0.061)	(0.376)			(0.282)	(1.603)
Sym Crypto			1.513***	0.572	1.490***	0.619	2.724***	-0.527	2.610***	-0.576
			(0.067)	(0.411)	(0.068)	(0.413)	(0.301)	(1.720)	(0.302)	(1.724)
Sym Degree	0.237***	0.162*	0.132***	0.118	0.156***	0.072	0.188***	-0.009	0.300***	0.060
	(0.011)	(0.068)	(0.012)	(0.071)	(0.013)	(0.082)	(0.052)	(0.284)	(0.059)	(0.325)
Log Num Txn			0.043***	0.038*	0.043***	0.038*	-0.033**	-0.054	-0.034**	-0.054
			(0.003)	(0.017)	(0.003)	(0.017)	(0.012)	(0.070)	(0.012)	(0.070)
Intercept	0.665***	0.252***	1.111***	0.344	1.111***	0.345	2.457***	0.447	2.454***	0.444
	(0.005)	(0.030)	(0.036)	(0.219)	(0.036)	(0.219)	(0.153)	(0.856)	(0.153)	(0.856)
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	0.0002	0.0002	0.0002	0.0002	0.0006	0.0015	0.0006	0.0015
Adj. R-Squared	0.00	0.00	0.0002	0	0.0002	0	0.0005	-0.0003	0.0006	-0.0003
Observations	33.22M	335.50K	33.22M	335.50K	33.22M	335.50K	3.12M	32.00K	3.12M	32.00K

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. Peer Diffusion of Crypto through Other Crypto Platforms (OCP)

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	0.451***	0.451***	0.451***	0.103**	0.100**	0.100**	0.097**
	(0.047)	(0.047)	(0.047)	(0.038)	(0.038)	(0.038)	(0.037)
Sym Treated			0.065**			-0.040*	
			(0.023)			(0.019)	
OCP	0.822	0.823	0.846	-0.599	-0.588	-0.571	-0.568
	(0.535)	(0.535)	(0.536)	(0.432)	(0.432)	(0.432)	(0.424)
OCP X Treated	0.243	0.242	0.240	-0.107	-0.118	-0.120	-0.115
	(0.538)	(0.538)	(0.538)	(0.434)	(0.434)	(0.434)	(0.426)
Sym OCP X Treated		0.123	0.123		1.359	1.360	1.350
		(0.902)	(0.902)		(0.727)	(0.727)	(0.714)
OCP X Sym Treated			-0.178			-0.128	
			(0.121)			(0.098)	
Sym Degree	0.257***	0.257***	0.224***	-0.000	-0.000	0.021	-0.002
	(0.009)	(0.009)	(0.015)	(0.007)	(0.007)	(0.012)	(0.007)
Sym Crypto	1.359***	1.359***	1.392***	0.284***	0.285***	0.263***	0.269***
	(0.067)	(0.067)	(0.068)	(0.054)	(0.054)	(0.055)	(0.053)
Sym OCP	-0.005	-0.127	-0.119	0.737***	-0.608	-0.608	-0.581
	(0.094)	(0.897)	(0.897)	(0.076)	(0.724)	(0.724)	(0.710)
Log Num Txn	0.042***	0.042***	0.042***	0.152***	0.152***	0.152***	0.148***
	(0.003)	(0.003)	(0.003)	(0.002)	(0.002)	(0.002)	(0.002)
Intercept	0.664***	0.664***	0.663***	0.068	0.071	0.072	0.061
	(0.058)	(0.058)	(0.058)	(0.047)	(0.047)	(0.047)	(0.046)
E(Y)	0.0007	0.0007	0.0007	0.0005	0.0005	0.0005	0.0005
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	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
Adj. R-Squared	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002	0.0002
Observations	33.56M	33.56M	33.56M	33.56M	33.56M	33.56M	33.56M

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 6. Impacts of the Legalization of Online Gambling

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) restrict the analysis to users who were selected for the crypto campaign, while Columns (5) and (6) 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 PayPal 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		Incentive Campaign Sample		Legalized Gambling Sample	
	Gamble Vol	Gamble Share	Gamble Vol	Gamble Share	Gamble Vol	Gamble Share
	(1)	(2)	(3)	(4)	(5)	(6)
Legalized	1.4649***	0.0036***	1.3539***	0.0038***	1.5691***	0.0037***
	(0.0063)	(0.0000)	(0.0057)	(0.0000)	(0.0083)	(0.00)
E(Y)	0.54	0.001	0.502	0.001	0.80	0.002
R-Squared	0	0.0006	0	0.0007	0	0.001
Adj. R-Squared	0	0.0006	0	0.0007	0	0.001
Observations	2.14B	2.14B	782.06M	782.06M	502.86M	502.86M

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.

Table 7. Peer Diffusion of Gambling Behavior Based on Legalization Natural Experiment

This table examines the impact of online gambling legalization on users' online gambling spending. Columns (1)–(4) analyze the full sample of users, while Columns (5)–(8) focus on the sub-sample of users selected for the crypto campaign experiment. The dependent variables are *Gamble Vol*$_{it}$, which represents the dollar amount of online gambling spending by user i during month t, and *Gamble Share*$_{it}$, which denotes the share of online gambling spending in the 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. Interaction terms include *Legalized X Sym Gamble*, which captures whether users with more symmetric (mutual) gambling connections respond differently to the legalization, and *Legalized X Sym Gamble = 1* and *Legalized X Sym Gamble ¿ 1*, which differentiate between having exactly one and more than one gambling friend. The regression is estimated using a Two-Way Fixed Effects (TWFE) model, which includes user fixed effects and year fixed effects.

	Full Gambling Sample				Incentive Campaign Sample			
	Gamble Vol		Gamble Share		Gamble Vol		Gamble Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Legalized	1.3739***	1.3697***	0.0033***	0.0033***	1.2599***	1.256***	0.0035***	0.0035***
	(0.0064)	(0.0064)	(0.0000)	(0.0000)	(0.0057)	(0.0057)	(0.0000)	(0.0000)
Legalized X Sym Gamble	7.7145***		0.0196***		6.4892***		0.0188***	
	(0.0469)		(0.0000)		(0.0373)		(0.0000)	
Legalized X Sym Gamble = 1		8.0726***		0.0205***		6.6903***		0.0193***
		(0.0613)		(0.0000)		(0.0491)		(0.0000)
Legalized X Sym Gamble >1		19.1963***		0.0493***		16.6449***		0.0483***
		(0.185)		(0.0000)		(0.1455)		(0.0001)
E(Y)	0.54	0.54	0.001	0.001	0.502	0.502	0.001	0.001
R-Squared	0	0	0.0009	0.001	0.0001	0.0001	0.001	0.001
Adj. R-Squared	0	0	0.0009	0.001	0.0001	0.0001	0.001	0.001
Observations	2.14B	2.14B	2.14B	2.14B	782.06M	782.06M	782.06M	782.06M

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.

Table 8. Peer Legalization on Gambling Volume

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 users residing in states that did not experience a gambling legalization shock 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)	(5)	(6)	(7)	(8)
Sym Legalized	0.467***	0.4587***			0.3919***	0.3881***	0.3852***	0.3781***
	(0.0269)	(0.0275)			(0.0274)	(0.0279)	(0.0279)	(0.0285)
Sym Legalized Adopted			1.7459***	1.7156***	1.4748***	1.4707***		
			(0.0992)	(0.0996)	(0.1009)	(0.1011)		
Sym Legalized X Sym Gamble							0.72***	0.7093***
							(0.065)	(0.0656)
Sym Legalized X Sym Crypto								0.1146
								(0.0943)
Sym Crypto Legalized		0.2043		0.4428***		0.0978		
		(0.1332)		(0.131)		(0.1334)		
E(Y)	0.1744	0.1744	0.1744	0.1744	0.1744	0.1744	0.1744	0.1744
R-Squared	0	0	0	0	0	0	0	0
Adj. R-Squared	0	0	0	0	0	0	0	0
Observations	1.63B	1.63B	1.63B	1.63B	1.63B	1.63B	1.63B	1.63B

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.

Table 9. Treated Peers with Gamble Controls

This table examines whether individuals' online gambling behavior and their gambling peers influence their responses to the experiment. Columns (1), (3), and (5) analyze the treatment group, while Columns (2), (4), and (6) analyze the control group. The key independent variable, The dependent variable in all columns is *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. *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. *Was Gamble* is an indicator for whether a user engaged in gambling before the experiment. Additional definations can be found in Appendix. All regressions control for age, income, and state fixed effects where indicated.

	Treatment	Control	Treatment	Control	Treatment	Control
	(1)	(2)	(3)	(4)	(5)	(6)
Sym Treated >0	0.438***	0.064			0.423***	0.039
	(0.027)	(0.168)			(0.027)	(0.169)
Sym Treated = 1			0.438***	0.064		
			(0.027)	(0.168)		
Sym Treated >1			0.260***	0.426		
			(0.061)	(0.380)		
Sym Gamble Treated >0	-0.544***	-0.581	-0.528***	-0.610	-0.087	0.050
	(0.110)	(0.714)	(0.110)	(0.714)	(0.144)	(0.929)
Gambled	0.833***	-0.333	0.832***	-0.331	0.852***	-0.309
	(0.048)	(0.297)	(0.048)	(0.297)	(0.048)	(0.298)
Sym Crypto	1.476***	0.580	1.455***	0.623	1.494***	0.611
	(0.067)	(0.414)	(0.067)	(0.416)	(0.067)	(0.415)
Sym Degree	0.135***	0.109	0.155***	0.067	0.147***	0.127
	(0.012)	(0.072)	(0.013)	(0.082)	(0.012)	(0.074)
Sym Gamble					-0.390***	-0.534
					(0.080)	(0.503)
Log Num Txn	0.039***	0.043*	0.039***	0.044*	0.039***	0.043*
	(0.003)	(0.017)	(0.003)	(0.017)	(0.003)	(0.017)
(Intercept)	1.095***	0.333	1.095***	0.333	1.095***	0.333
	(0.036)	(0.222)	(0.036)	(0.222)	(0.036)	(0.222)
E(Y)	0.0007	0.0003	0.0007	0.0003	0.0007	0.0003
Age	Y	Y	Y	Y	Y	Y
Income	Y	Y	Y	Y	Y	Y
State	Y	Y	Y	Y	Y	Y
R-Squared	0.0002	0.0002	0.0002	0.0002	0.0003	0.0002
Adj. R-Squared	0.0002	0.0000	0.0002	0.0000	0.0002	0.0000
Observations	33.27M	335.98K	33.27M	335.98K	33.27M	335.98K

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 10. Peer Diffusion of Crypto Behavior Based on Legalization Natural Experiment

This table examines the impact of online gambling legalization on users' crypto purchase volume. Columns (1)–(4) analyze the full sample of users, while Columns (5)–(8) focus on the sub-sample of users who ever used crypto in our sample period. The dependent variables are *Crypto* Vol_{it}, which represents the dollar amount of crypto purchase by user i during month t, and *Crypto* $Share_{it}$, which denotes the share of crypto purchase in the 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. Interaction terms include *Legalized X Sym Gamble*, which captures whether users with more symmetric (mutual) gambling connections respond differently to the legalization, and *Legalized X Sym Gamble = 1* and *Legalized X Sym Gamble ¿ 1*, which differentiate between having exactly one and more than one gambling friend. The regression is estimated using a Two-Way Fixed Effects (TWFE) model, which includes user fixed effects and year fixed effects.

	Full Gambling Sample				Crypto User Sample			
	Crypto Vol		Crypto Share		Crypto Vol		Crypto Share	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Legalized	-0.1303***	-0.1283***	-0.0001***	-0.0001***	-7.6251***	-7.5498***	-0.0037***	-0.0037***
	(0.0108)	(0.0108)	(0.0000)	(0.0000)	(0.7405)	(0.7422)	(0.0002)	(0.0002)
Legalized X Sym Gamble	-1.7113***		-0.0011***		-16.0359***		-0.0063***	
	(0.0788)		(0.0000)		(3.1878)		(0.0009)	
Legalized X Sym Gamble = 1		-1.9424***		-0.0014***		-19.0741***		-0.0092***
		(0.1029)		(0.0000)		(4.512)		(0.0012)
Legalized X Sym Gamble >1		-3.8914***		-0.0021***		-40.276***		-0.0093**
		(0.3107)		(0.0000)		(11.632)		(0.0032)
E(Y)	0.70	0.70	0.0008	0.0008	47.82	47.82	0.05	0.05
R-Squared	0	0	0.0009	0.001	0.0001	0.0001	0.001	0.001
Adj. R-Squared	0	0	0.0009	0.001	0.0001	0.0001	0.001	0.001
Observations	2.14B	2.14B	2.14B	2.14B	31.06M	31.06M	31.06M	31.06M

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.

Table 11. Peer Legalization on Crypto Volume

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 a sample of users residing in states that did not experience a gambling legalization shock and who had not engaged in gambling prior to the first legalization shock. The dependent variable, *Crypto* Vol_{it}, represents the dollar amount of cryptocurrency purchased by user i during month t. The key explanatory variable, *Sym* $Legalized_t$, is an indicator equal to 1 if gambling was legalized in the state of the user's first friend in their network. *Sym Legalized* $Adopted_t$ captures whether the user's first friend in their network resides in a state where gambling was legalized and subsequently started gambling. *Sym Gamble* measures the number of gambling friends a user has. The interaction term *Sym Legalized X Sym Gamble* assesses whether having a greater number of gambling friends amplifies the effect of gambling legalization on crypto purchasing behavior. The regression is estimated using a Two-Way Fixed Effects (TWFE) model, which includes user fixed effects and year fixed effects.

	Crypto Vol			
	(1)	(2)	(3)	(4)
Sym Legalized	-1.3843***		-1.2329***	-1.2507***
	(0.0538)		(0.0548)	(0.0558)
Sym Legalized Adopted		-3.8268***	-2.9739***	
		(0.1984)	(0.202)	
Sym Legalized X Sym Gamble				-1.1753***
				(0.1301)
Intercept	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
E(Y)	0.6745	0.6745	0.6745	0.6745
R-Squared	0	0	0	0
Adj. R-Squared	0	0	0	0
Observations	1.63B	1.63B	1.63B	1.63B

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.

Table 12. Peer Diffusion of Total Transaction Behavior Based on Legalization Natural Experiment

This table examines the impact of online gambling legalization on individuals' total transaction volumes. Columns (1)–(4) analyze total transaction volumes for the full sample, while Columns (5)–(8) focus on users who were selected for the crypto campaign experiment. The dependent variables are *Total Vol*$_{it}$, which represents the total transaction volume for user i during month t, and *Log Total Vol*$_{it}$, which is the natural logarithm of the total 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 regression is estimated using a Two-Way Fixed Effects (TWFE) model, which includes user fixed effects and year fixed effects.

	Full Sample				Incentive Campaign Sample			
	Total Volume		Log Total Volume		Total Volume		Log Total Volume	
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Legalized	1.6743***	1.6714***	0.0131***	0.0131***	1.4307***	1.4218***	0.0104***	0.0103***
	(0.0284)	(0.0284)	(0.0002)	(0.0002)	(0.0375)	(0.0375)	(0.0003)	(0.0003)
Legalized X Sym Gamble	4.8638***		0.0573***		6.8563***		0.0875***	
	(0.2066)		(0.0012)		(0.2457)		(0.0019)	
Legalized X Sym Gamble = 1		5.1431***		0.0574***		7.6592***		0.0973***
		(0.2698)		(0.0016)		(0.3224)		(0.0025)
Legalized X Sym Gamble >1		11.8579***		0.1526***		16.0193***		0.2052***
		(0.8143)		(0.0048)		(0.957)		(0.0073)
E(Y)	62.16	62.16	1.458	1.458	60.51	60.51	1.545	1.545
R-Squared	0	0	0	0	0	0	0	0
Adj. R-Squared	0	0	0	0	0	0	0	0
Observations	2.14B	2.14B	2.14B	2.14B	782.35M	782.35M	782.35M	782.35M

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.

A Appendix A: Additional Analyses

Table A1: Balance Table for First Campaign

	Trt. Mean	Trt. SD	Ctl. Mean	Ctl. SD	p-Value
Symmetric Degree	0.1582	0.5828	0.1581	0.58	0.9093
Symmetric Crypto	0.0049	0.0722	0.005	0.073	0.7193
Symmetric Coinbase	0.0025	0.0508	0.0025	0.0518	0.6111
Symmetric Gamble	0.0049	0.0804	0.0047	0.0787	0.1736
Number of Total Transactions Per Year	55.9473	101.1788	56.1603	102.2705	0.2252
Total Transaction Volume Per Year	3,106.21	5,803.38	3,102.94	5,792.99	0.746
Number of P2P Transactions Per Year	5.1787	20.1976	5.1908	20.1523	0.7299
P2P Transaction Volume Per Year	691.5911	3,029.00	688.8858	2,978.91	0.6067
Number of Retail Transactions Per Year	25.4183	47.6243	25.5327	48.2136	0.1662
Retail Transaction Volume Per Year	1,206.60	2,272.94	1,206.07	2,269.50	0.8938
Fraction of People Ever Gambled	0.0099	0.0988	0.0099	0.099	0.838
Fraction of People Ever used Coinbase	0.0078	0.0877	0.0076	0.0868	0.2854
Age: 50+	0.2543	0.4355	0.2545	0.4356	0.7627
Age: 30-49	0.429	0.4949	0.4295	0.495	0.5484
Age: 18-29	0.3167	0.4652	0.316	0.4649	0.3569
Income: >$125K	0.1315	0.338	0.131	0.3374	0.339
Income: $50-125K	0.4512	0.4976	0.4507	0.4976	0.5823
Income: <$50K	0.4173	0.4931	0.4183	0.4933	0.2262

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 A2: Balance Table for Second Campaign

	Trt. Mean	**Trt. SD**	**Ctl. Mean**	**Ctl. SD**	**p-Value**
Symmetric Degree	0.3637	0.9182	0.3642	0.9173	0.6486
Symmetric Crypto	0.0119	0.1132	0.0122	0.1143	0.0836
Symmetric Coinbase	0.0061	0.0802	0.0061	0.0796	0.4379
Symmetric Gamble	0.0133	0.1383	0.0134	0.1394	0.6829
Number of Total Transactions Per Year	109.608	140.51	109.5526	141.2006	0.7665
Total Transaction Volume Per Year	5,570.76	7,699.45	5,574.67	7,701.04	0.7017
Number of P2P Transactions Per Year	9.8239	28.9275	9.7697	27.5411	0.1572
P2P Transaction Volume Per Year	1,287.98	4,112.02	1,294.91	4,162.68	0.2039
Number of Retail Transactions Per Year	49.2782	66.1947	49.2684	66.7909	0.9114
Retail Transaction Volume Per Year	2,109.40	2,975.71	2,107.67	2,966.19	0.6608
Fraction of People Ever Gambled	0.0246	0.155	0.0249	0.1559	0.1796
Fraction of People Ever used Coinbase	0.015	0.1215	0.0149	0.1213	0.7514
Age: 50+	0.2117	0.4085	0.2122	0.4089	0.2821
Age: 30-49	0.4951	0.5	0.4945	0.5	0.3981
Age: 18-29	0.2933	0.4553	0.2932	0.4552	0.9704
Income: >$125K	0.1283	0.3345	0.1283	0.3344	0.9347
Income: $50-125K	0.4381	0.4962	0.4389	0.4963	0.2287
Income: <$50K	0.4335	0.4956	0.4328	0.4955	0.2502

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 A3: Adoption of Crypto in the Second Incentive Experiment

	Full Experiment Sample			Attentive Users	
	(1)	(2)	(3)	(4)	(5)
Treated	0.147***	0.147***	0.147***	0.297	0.296
	(0.037)	(0.037)	(0.037)	(0.180)	(0.180)
Treated Q1	-0.098***	-0.098***	-0.096***	-1.137***	-1.136***
	(0.017)	(0.017)	(0.017)	(0.105)	(0.105)
Sym Crypto	0.751***			1.380***	
	(0.072)			(0.353)	
Sym Crypto >1		1.699***	1.695***		3.494
		(0.396)	(0.396)		(1.869)
Sym Crypto = 1		0.746***	0.745***		1.361***
		(0.077)	(0.077)		(0.382)
Sym Degree	0.034***	0.034***	0.034***	0.015	0.01
	(0.009)	(0.009)	(0.009)	(0.047)	(0.048)
Was Gamble			0.671***		1.321***
			(0.052)		(0.274)
Has Sym Gamble			-0.112		-0.0095
			(0.078)		(0.4074)
Log Num Txn	-0.064***	-0.064***	-0.067***	-0.124***	-0.124***
	(0.005)	(0.005)	(0.005)	(0.024)	(0.024)
Intercept	1.257***	1.257***	1.262***	2.604***	2.604***
	(0.069)	(0.069)	(0.069)	(0.331)	(0.331)
E(Y)	0.0008	0.0008	0.0008	0.0014	0.0014
Age	Y	Y	Y	Y	Y
Income	Y	Y	Y	Y	Y
State	Y	Y	Y	Y	Y
R-Squared	0	0	0	0.0004	0.0004
Adj. R-Squared	0	0	0	0.0003	0.0003
Observations	12.55M	12.55M	12.55M	950.36K	950.36K

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 A4: 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	0.447***	0.431	0.678***	-0.121	0.606***	-0.177	0.203***	0.577
	(0.037)	(0.227)	(0.086)	(0.593)	(0.073)	(0.372)	(0.052)	(0.385)
High Age Sym Treated >0	0.066	-0.962**	-0.008	-0.494	0.089	-0.244	-0.108	-1.032
	(0.052)	(0.321)	(0.1)	(0.701)	(0.089)	(0.449)	(0.095)	(0.483)
Mid Age Sym Treated >0	-0.06	-0.457	-0.366***	0.937	-0.092	0.283	-0.025	-1.321**
	(0.041)	(0.257)	(0.095)	(0.661)	(0.078)	(0.395)	(0.065)	(0.483)
Sym Crypto	1.482***	0.543	1.045***	-0.538	1.824***	-0.345	1.147***	2.3**
	(0.067)	(0.415)	(0.136)	(0.971)	(0.105)	(0.521)	(0.115)	(0.846)
Sym Degree	0.136***	0.145*	0.097***	0.095	0.089***	0.07	0.255***	0.3
	(0.012)	(0.074)	(0.023)	(0.162)	(0.018)	(0.09)	(0.022)	(0.166)
Log Num Txn	0.043***	0.041*	0.056***	0.064*	0.033***	-0.007	0.044***	0.091*
	(0.003)	(0.017)	(0.004)	(0.03)	(0.005)	(0.023)	(0.005)	(0.037)
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	0.0002	0.0003	0.0002	0.0009	0.0002	0.0004	0.0002	0.0008
Adj. R-Squared	0.0002	0	0.0001	0.0002	0.0002	0	0.0002	0.0002
Observations	33.27M	335.98K	8.46M	85.53K	14.27M	144.28K	10.54M	106.18K

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 A5: Income Heterogeneity of Treated Peers

	Full Experiment Sample		High Income Sample		Mid Income Sample		Low Income Sample	
	Trt.	Ctl.	Trt.	Ctl.	Trt.	Ctl.	Trt.	Ctl.
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
Sym Treated >0	0.762***	0.243	0.588***	-1.764***	0.562***	-0.275	0.792***	0.639*
	(0.032)	(0.2)	(0.08)	(0.522)	(0.047)	(0.313)	(0.053)	(0.312)
High Income Sym Treated >0	-0.773***	-0.345	-0.476***	2.13***	-0.478***	-0.069	-0.922***	-1.319
	(0.06)	(0.373)	(0.096)	(0.628)	(0.079)	(0.532)	(0.134)	(0.794)
Medium Income Sym Treated >0	-0.665***	-0.393	-0.629***	1.815**	-0.339***	0.172	-0.793***	-0.849*
	(0.039)	(0.242)	(0.092)	(0.601)	(0.053)	(0.354)	(0.07)	(0.41)
Sym Crypto	1.441***	0.552	0.684***	-0.96	0.928***	-0.245	2.025***	1.448*
	(0.067)	(0.415)	(0.139)	(1.006)	(0.09)	(0.593)	(0.117)	(0.673)
Sym Degree	0.179***	0.127	0.102***	0.27	0.107***	0.014	0.273***	0.174
	(0.012)	(0.073)	(0.022)	(0.142)	(0.015)	(0.101)	(0.022)	(0.13)
Log Num Txn	0.042***	0.041*	0.046***	0.04	0.044***	0.024	0.038***	0.063*
	(0.003)	(0.017)	(0.005)	(0.032)	(0.004)	(0.023)	(0.005)	(0.031)
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	0.0002	0	0.0013	0	0.0002	0.0002	0.0006
Adj. R-Squared	0.0002	0	0	0	0	-0.0002	0.0002	0.0002
Observations	33.27M	335.98K	4.37M	43.95K	15.01M	151.44K	13.89M	140.59K

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.

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.
Gambled	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.

Table B1: Variable Description

Variable	**Description**
Panel Variables	
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 Legalized Adopted	A binary indicator variable equal to 1 once any of the user's friends' state legalized online gambling and the friend started gambling in month t, and 0 otherwise.
Sym Crypto	The number of friends who ever purchased crypto before the end of the sample.
Sym Gamble	The number of friends who ever gambled before the end of the sample.
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 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 Variables	
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.
Gamble Legalization Users	This sample consists the PayPal users who were selected in the first PayPal marketing experiment and who created their account before November 2020. In other words, this sample is the overlap sample of the campaign experiment and the gambling nature experiment.
Panel Variables	
Full Gambling Sample	This sample consists of all PayPal users who created their accounts prior to November 2020, 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 PayPal 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.
Incentive Campaign Sample	This sample consists individuals who were selected for the campaign and had created their accounts prior to November 2020.

7 Pending Tables

Pending Table 1: Treated Peers - Columns 5 and 6

	Adopted Crypto	
	Trt.	Ctl.
	(5)	(6)
Sym Treated >0	0.595***	0.14
	(0.123)	(0.691)
Sym Crypto	2.648***	-0.522
	(0.301)	(1.713)
Sym Degree	0.191***	-0.008
	(0.052)	(0.284)
Log Num Txn	-0.034**	-0.054
	(0.012)	(0.07)
E(Y)	0.0013	0.0004
Age	Y	Y
Income	Y	Y
State	Y	Y
R-Squared	0.0006	0.0015
Adj. R-Squared	0.0005	-0.0003
Observations	3.13M	32.05K

Pending Table 2: Treated Peers with Gamble Controls

	Adopted Crypto					
	Trt.	Ctl.	Trt.	Ctl.	Trt.	Ctl.
	(1)	(2)	(3)	(4)	(5)	(6)
Sym Treated >0	0.438***	0.064			0.423***	0.039
	(0.027)	(0.168)			(0.027)	(0.169)
Sym Treated >1			0.260***	0.426		
			(0.061)	(0.380)		
Sym Treated = 1			0.438***	0.064		
			(0.027)	(0.168)		
Sym Gamble Treated >0	-0.544***	-0.581	-0.528***	-0.610	-0.087	0.050
	(0.110)	(0.714)	(0.110)	(0.714)	(0.144)	(0.929)
Was Gamble	0.833***	-0.333	0.832***	-0.331	0.852***	-0.309
	(0.048)	(0.297)	(0.048)	(0.297)	(0.048)	(0.298)
Sym Crypto	1.476***	0.580	1.455***	0.623	1.494***	0.611
	(0.067)	(0.414)	(0.067)	(0.416)	(0.067)	(0.415)
Sym Degree	0.135***	0.109	0.155***	0.067	0.147***	0.127
	(0.012)	(0.072)	(0.013)	(0.082)	(0.012)	(0.074)
Sym Gamble					-0.390***	-0.534
					(0.080)	(0.503)
Log Num Txn	0.039***	0.043*	0.039***	0.044*	0.039***	0.043*
	(0.003)	(0.017)	(0.003)	(0.017)	(0.003)	(0.017)
(Intercept)	1.095***	0.333	1.095***	0.333	1.095***	0.333
	(0.036)	(0.222)	(0.036)	(0.222)	(0.036)	(0.222)
E(Y)	0.0007	0.0003	0.0007	0.0003	0.0007	0.0003
Age	Y	Y	Y	Y	Y	Y
Income	Y	Y	Y	Y	Y	Y
State	Y	Y	Y	Y	Y	Y
R-Squared	0.0002	0.0002	0.0002	0.0002	0.0003	0.0002
Adj. R-Squared	0.0002	0.0000	0.0002	0.0000	0.0002	0.0000
Observations	33.27M	335.98K	33.27M	335.98K	33.27M	335.98K

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.

Pending Table 3: Legalization on Crypto

	Crypto Vol	Crypto Share	Crypto Vol	Crypto Share	Log Crypto Vol
	All (1)	All (2)	Crypto (3)	Crypto (4)	Crypto (5)
Has Legalized	-0.1533***	-0.00009***	-8.1928***	-0.0043***	-0.0318***
	(0.0109)	(0.0000)	(0.7477)	(0.0002)	(0.0012)
(Intercept)	0.00	0.00	0.00	0.00	0.00
	(0.0000)	(0.0000)	(0.1595)	(0.0000)	(0.0003)
E(Y)	0	0	0	0	0
R-Squared	0	0	0	0	0
Adj. R-Squared	0	0	0	0	0
Observations	1.71B	1.71B	24.72M	24.72M	24.72M

Pending Table 4: Legalization on Crypto - Heterogeneity

	Crypto Share				Log Crypto Vol	
	(1) All	(2) All	(3) Crypto	(4) Crypto	(5) Crypto	(6) Crypto
Has Legalized	-0.00008***	-0.00007***	-0.0046***	-0.0044***	-0.0339***	-0.032***
	(0.00)	(0.00)	(0.0002)	(0.0002)	(0.0012)	(0.0012)
Has Legalized X Sym Crypto	-0.0016***	-0.0014***	0.0097***	0.0109***	0.0775***	0.0883***
	(0.00)	(0.00)	(0.0011)	(0.0011)	(0.0064)	(0.0064)
Has Legalized X Sym Gamble		-0.001***		-0.0072***		-0.0672***
		(0.00)		(0.0009)		(0.0052)
(Intercept)	0.00	0.00	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)	(0.0002)	(0.0002)
E(Y)	-3.34E-40	-3.34E-40	-3.10E-40	-3.10E-40	-7.42E-39	-7.42E-39
R-Squared	0	0	0	0	0	0
Adj. R-Squared	0	0	0	0	0	0
Observations	1.71B	1.71B	24.72M	24.72M	24.72M	24.72M

Pending Table 5: Legalization on Retail Transaction

	Retail Transac Vol	Retail Transac Share	Retail Transac Vol	Retail Transac Share	Log Retail Transac Vol
	(1) All	(2) All	(3) Crypto	(4) Crypto	(5) Crypto
Has Legalized	0.7652***	-0.0011***	-0.0848	-0.0067***	-0.004**
	(0.0246)	(0.00)	(0.2714)	(0.0003)	(0.0015)
(Intercept)	0.00	0.00	0.00	0.00	0.00
	(0.0048)	(0.00)	(0.054)	(0.00)	(0.0003)
E(Y)	1.72E-10	4.10E-39	3.44E-10	-2.92E-39	2.42E-10
R-Squared	0	0	0	0	0
Adj. R-Squared	0	0	0	0	0
Observations	1.71B	1.71B	24.72M	24.72M	24.72M

Pending Table 6: Legalization on Retail Transaction - Heterogeneity

	Retail Transaction Share			
	(1) All	(2) All	(3) All	(4) All
Has Legalized	-0.001***	-0.0009***	-0.0061***	-0.0058***
	(0.00)	(0.00)	(0.0003)	(0.0003)
Has Legalized X Sym Crypto	-0.0116***	-0.01***	-0.0229***	-0.0212***
	(0.0004)	(0.0004)	(0.0018)	(0.0018)
Has Legalized X Sym Gamble		-0.0072***		-0.011***
		(0.0003)		(0.0014)
(Intercept)	0.00	0.00	0.00	0.00
	(0.00)	(0.00)	(0.00)	(0.00)
E(Y)	4.10E-39	4.10E-39	-2.92E-39	-2.92E-39
R-Squared	0	0	0	0
Adj. R-Squared	0	0	0	0
Observations	1.71B	1.71B	24.72M	24.72M

Pending Table 7: Peer Legalization on Gamble

	Gamble Volume		
	(1) All	(2) All	(3) All
Sym Legalized	0.8138***	0.7779***	0.7097***
	(0.0809)	(0.0838)	(0.0868)
Sym Legalized X Has Sym Crypto		0.5247	
		(0.3188)	
Sym Legalized Nov X Sym Crypto			0.21
			(0.2869)
Sym Legalized Nov X Sym Gamble			0.5338***
			(0.1604)
(Intercept)	0.00	0.00	0.00
	(0.0039)	(0.0039)	(0.0039)
E(Y)	-5.52E-10	-5.52E-10	-5.52E-10
R-Squared	0	0	0
Adj. R-Squared	0	0	0
Observations	224.50M	224.50M	224.50M

Pending Table 8: Peer Legalization on Retail

	Retail Transaction Volume		
	(1) All	(2) All	(3) All
Sym Legalized	2.4685***	2.5416***	2.7145***
	(0.2685)	(0.2782)	(0.2881)
Sym Legalized X Has Sym Crypto		-1.0668	
		(1.0589)	
Sym Legalized X Sym Crypto			-0.6274
			(0.9527)
Sym Legalized X Sym Gamble			-1.2027*
			(0.5328)
(Intercept)	0.00	0.00	0.00
	(0.0129)	(0.0129)	(0.0129)
E(Y)	3.79E-10	3.79E-10	3.79E-10
R-Squared	0	0	0
Adj. R-Squared	0	0	0
Observations	224.50M	224.50M	224.50M