The Effects of Cryptocurrency Wealth on Household Consumption and Investment*

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Abstract

This paper uses transaction-level bank and credit card data to identify cryptocurrency investors and assess the impact of crypto wealth fluctuations on household consumption, as well as on investments in other assets. We find an $0.09 MPC from crypto gains, exceeding most previous estimates from unrealized equity gains. However, crypto investors are mostly also active equity investors, with many similar consumption patterns across gains from both asset classes. Households sell cryptocurrencies to increase discretionary and housing expenditures, with the latter causing local house price appreciation.

Keywords: cryptocurrency, Bitcoin, Ethereum, consumption, transaction data, household balance sheet, real estate

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1 Introduction

In the last decade, cryptocurrencies have gone from relative obscurity to a peak global market capitalization of over $3 trillion. Households in the U.S. have increasingly adopted crypto as part of their investment portfolio and crypto's extreme volatility has led to rapid wealth gains for many investors. While the cryptocurrency market has experienced rapid adoption and growth, it is unclear whether how households treat this asset class relative to other traditional investments and whether cryptocurrency drives spillovers to the broader economy. While some attention has focused on crypto and financial stability, lack of data due to the anonymous nature of transactions on public blockchains has restricted research regarding how the introduction of cryptocurrencies has affected the investment and consumption behavior of individual households and how it has spilled over into other asset classes.

In this paper, we use transaction-level data spanning millions of U.S. households' bank accounts and credit cards to analyze how crypto wealth impacts the real economy. Specifically, we are able to trace how household consumption responds to changes in crypto wealth and to assess the causal effect of this wealth on real asset prices. We identify crypto users based on transfers into and out of major cryptocurrency exchanges and impute crypto wealth based on the timing of these transactions. While most crypto users have invested relatively small amounts into this asset class, many individuals have the equivalent of several months of consumption held in such accounts (consistent with findings in Wheat and Eckerd, 2022).

We begin by briefly summarizing the characteristics of crypto users by linking a large, nationally representative set of U.S. households with a complete set of financial transactions. This allows us to compare the income and spending patterns of crypto users to non-crypto users. We more fully characterize the decision to invest in crypto in Aiello, Baker, Balyuk, Di Maggio, Johnson, and Kotter (2023). In this paper, we focus primarily on the effect of crypto gains on consumption and investment decisions. We find that crypto adopters have higher incomes, which matches recent survey evidence (Benetton and Compiani, 2024), and are more likely to deposit money in traditional equity brokerages than non-adopters.

On average, households appear to treat crypto as one asset class within a larger investment portfolio. Crypto users are more likely to be active traders in equity markets, often simultaneously investing in both crypto assets and traditional equity securities. We also find evidence suggesting that households re-balance their portfolios by selling crypto after large gains and depositing money into traditional brokerages.

We then turn to the key results of the paper, examining how spending patterns change following changes in crypto wealth. We estimate a marginal propensity to consume (MPC) out of crypto wealth of $0.09. Qualitatively, this mirrors consumption responses to the appreciation of other asset classes such as housing (e.g., Carroll, Otsuka, and Slacalek, 2011; Aladangady, 2017) and equities (e.g., Hartzmark and Solomon, 2019; Di Maggio, Kermani, and Majlesi, 2020), but is about two times larger. At the same time, the MPC is roughly one-third the estimated MPC from one-time income shocks (e.g., economic stimulus payments in Kaplan and Violante (2014); Johnson, Parker, and Souleles (2006)) and is much smaller than those found in studies of lottery winnings, which range from 50% to 100% (e.g., Fagereng, Holm, and Natvik, 2021).

Differences in consumption out of crypto wealth can be driven both by the characteristics of the asset class and by the type of investors that participate in crypto markets. To tease this out, we estimate the MPC out of unrealized equity wealth for both crypto and non-crypto investors. We show that much of the differences in consumption are driven by investor type; the MPC out of crypto wealth is only modestly higher than the MPC out of equity wealth for crypto investors. In addition, for both equity and crypto gains, the MPC is significantly larger for constrained households with low savings. On net, households appear to treat cryptocurrencies similarly to more traditional after-tax equity investments.

Overall, our MPC estimates imply that the aggregate effect of increases in retail crypto wealth for the households in our sample implies an approximate \$30 billion increase in consumption.[1] If the consumption out of non-retail crypto gains is similar to our estimates, the total U.S. effect peaked at between \$70–\$100 billion in early 2021.[2]

While some of this increased consumption comes in the form of discretionary spending, we show that following large crypto withdrawals households transition from renters to homeowners at higher rates. These individual-level changes in housing consumption create an additional path for crypto returns to spill over into the local real economy—increased demand for homes can create local housing price pressure. Consequently, volatility in crypto markets can influence not just crypto investors but also the broader population. However, two challenges make it difficult to estimate the effect of crypto wealth on house prices. Naïve regression estimates potentially suffer from reverse causality, as higher prices might cause households to withdraw crypto investments in order to afford a home. Additionally, counties that become wealthier are likely to simultaneously invest more in all assets. We deal with these concerns by estimating the causal impact of county-level crypto wealth on local house price growth using two separate natural experiments.

The first experiment exploits the largest run-up in Bitcoin prices in our sample period (late-2017) as a shock to the crypto wealth in a county. Counties that had high per capita crypto wealth prior to the beginning of the price run-up were highly exposed to a quasi-random 12-month Bitcoin return of over 1,400%. To alleviate some concerns of reverse causality, we use a difference-in-differences methodology, noting an absence of differential trends in the period preceding the run-up in prices. To further alleviate concerns that changes in equity wealth (rather

[1] The total crypto wealth accumulated in our sample reached a peak of \$2,600 per household. Multiplying this by the number of US households (130 M) and the MPC of \$0.088 yields \$29.7B.

[2] Assuming that the U.S. holds between one-third to one-half of the world's crypto wealth, which is in line with estimates of the U.S. share of total household wealth.

than crypto wealth) drive our results, we show that following the Bitcoin price shock, high crypto wealth counties experience no change in traditional brokerage withdrawals, but experience a sharp increase in crypto withdrawals. House prices in high crypto wealth counties grow about 43 basis points faster than house prices in low crypto wealth counties, explaining roughly 11% of the standard deviation in house price growth.

We extend the concept underlying the difference-in-differences estimation to the full time series using a two-stage least squares (2SLS) specification based on an approach mirroring that used by Calvet, Campbell, and Sodini (2009) for studying equity market investors. We use passive gains in county-level crypto wealth, defined as the value of county crypto wealth 12-months prior grown by the annual return to Bitcoin and Ethereum, as an instrument for the growth in the county's crypto wealth. Because this instrument is based on historical crypto portfolios, it alleviates concerns about reverse causality stemming from individuals potentially adjusting their investments in response to near-term spending plans. The quasi-random nature of crypto returns makes it unlikely that most sources of wealth are simultaneously correlated with both crypto returns and historical county-level crypto wealth. While crypto returns are positively correlated with equity market returns in some periods, our 2SLS results are robust to controlling for county-level changes in equity wealth and using crypto returns in excess of market equity returns.

Increases in crypto wealth cause significant house price growth. The estimates suggest that an additional dollar of per capita county-level retail crypto wealth increases county house prices by about $0.15 over the following three months. To interpret this magnitude, consider that crypto gains lead investors to withdraw large amounts of cash from their crypto brokerages. Extrapolating from our data to the entire U.S. population, about 2.8 million households withdraw at least $5,000 worth of crypto between 2018 and 2023. While not all of these households will purchase homes, this is a meaningful increase in potential demand—roughly 10.5% relative to the total number of new home listings over that period. At the county level, a one standard deviation increase in per capita retail crypto gains leads to a $460 dollar increase in house prices over the next three months.

Unlike papers which describe characteristics of cryptocurrency investors or crypto trading behavior (e.g., Benetton and Compiani, 2024; Chava, Hu, and Paradkar, 2022; Divakaruni and Zimmerman, 2023; Hackethal, Hanspal, Lammer, and Rink, 2022; Makarov and Schoar, 2021), we examine the interaction of cryptocurrency price fluctuations with household consumption and investment behavior. Our data allow us to link a broad set of U.S. retail crypto traders to a relatively complete set of other financial transactions. One related study is Kogan, Makarov, Niessner, and Schoar (2023) which uses transaction-level data to characterize the investment decisions of retail crypto users. Kogan et al. (2023) observe actual crypto and equity trades and document momentum in crypto investment. Their ability to observe individual transactions and holdings across both asset classes allows them to shed light on the differences between equity and crypto investment decisions, while our ability to observe income, consumption, and real outcomes allows us to speak to the way households treat gains across these two asset classes.

Our paper also contributes to a large literature that assesses the impact of changes in income or asset prices on consumption behavior. Baker, Nagel, Wurgler, et al. (2007), Hartzmark and Solomon (2019), and Di Maggio, Kermani, and Majlesi (2020) look at equity markets and find that the MPC out of capital gains is on the order of 0.04. Case, Quigley, and Shiller (2005), Aladangady (2017), Berger, Guerrieri, Lorenzoni, and Vavra (2018), and Chen, Michaux, and Roussanov (2020) examine consumption responses to changes in home values and broadly find the MPC out of housing wealth to be roughly in line with capital gains. Beyond asset price fluctuations, there is also a large body of work that assesses the MPC out of shocks to either persistent or transitory income (e.g., Jappelli and Pistaferri, 2014; Agarwal and Qian, 2014; Baker, 2018; Baker, Farrokhnia, Meyer, Pagel, and Yannelis, 2020).

Comparing these consumption decisions to the those following equity or housing gains sheds light on how households treat crypto relative to other asset classes. Moreover, we leverage regional wealth shocks to test spatial variation in economic impacts, akin to work such as Chodorow-Reich, Nenov, and Simsek (2021), Hartman-Glaser, Thibodeau, and Yoshida (2023), and Griffin, Kruger, and Mahajan (2023) who exploit such regional variation in wealth changes to study consumption and house prices.

The rest of the paper proceeds as follows. Section 2 describes our transaction-level data set. Section 3 explores the role crypto plays in household investment decisions. Section 4 examines consumption responses to crypto wealth at the household level. Section 5 presents estimates of the causal effect of county-level crypto wealth on local house prices. Section 6 concludes.

2 Data

2.1 Transaction Data

Our data provider is a large financial aggregation and analytics firm that specializes in utilizing anonymized bank, credit, and debit card transaction data across millions of American households. This provider contracts primarily with financial institutions and FinTech firms to provide data and personal financial management services to their customers and an ability to aggregate financial information across a user's financial accounts. As a consequence, conditional on banking with a given financial institution, there is no additional selection of users into the database and attrition is minimal.

Our data are limited to bank, credit card, and debit card transactions, excluding transactions made *within* other types of accounts (e.g., brokerage accounts), though we can generally observe deposits *to* and withdrawals *from* those accounts. Each individual transaction contains a number of pieces of information. For instance, we are able to observe the precise date and amount of a transaction and whether the transaction was made in person or remotely. Using information from the textual description accompanying the transaction, transactions are categorized into one of 43 different categories (e.g. salary, ATM withdrawal, groceries, mortgage payments, medical spending). Merchant names and physical locations at a city or zip code level are also observable for the majority of transactions.

The full database spans over 60 million American users and billions of transactions from June 2010 until September 2023. The database experiences a substantial expansion of users in the early years, so we focus on data from 2014 onward to mitigate concerns about changes in the population. While these data allow us to see substantial detail surrounding users' financial transactions, we do not observe demographic information such as age, gender, or race. However, for a large fraction of users, we are able to impute the zip code of their residence based on the physical location of merchants that frequently appear in transactions.[3]

2.1.1 Validation of Consumer Transaction Data

Due to its size and granularity, transaction data from a variety of different providers has been increasingly utilized in research to answer questions about the behavior of individuals and the broader economy. Baker and Kueng (2022) provide a review of literature involving transaction data and some of the advantages and disadvantages inherent in its use. Balyuk and Williams (2023) utilize the same data provider as in this paper to study the rollout of peer-to-peer financial

[3]This imputed zip code represents the zip code in which they most frequently are seen making physical spending transactions in a given year. We limit these transactions to Grocery, Restaurant, Gasoline, General Merchandise, Home Improvement, and Pharmacy transactions.

transfer technology and Di Maggio, Williams, and Katz (2022) use these data to study buy now, pay later financing.

While our data are not drawn randomly from the population, in general it appears to be highly representative of the broader economy. Many other transaction databases have samples derived from a highly selected sample of the general population (e.g., those interested in using a FinTech app to borrow or to help pay down debt). In contrast, our data provider works with large financial institutions that cover a sizable fraction of the U.S. population, limiting worries about a highly selected sample.

To validate that the data are broadly representative, we compare our observed spending data to data obtained from merchants in the Census Retail Sales Surveys. These surveys are used by the Census Bureau to estimate monthly retail sales in the U.S. by merchant category. In Figure 1, we aggregate observable transactions from our data to a monthly level for a range of categories (Auto and Gas, General Merchandise, Groceries, Personal/Family, Medical, and Restaurants). The figure shows that trends in spending from 2015 to 2023 are very similar across our data and the Census Retail Sales survey. On average, the correlation in monthly spending from these two sources is over 0.90. The series with the lowest correlation, Healthcare and Medical, is also the category in which we would expect the largest share of pre-tax or third-party spending, driving a wedge between observable spending among households and revenue reported by retailers. The data also appears to be broadly representative across counties. In Appendix Figure A.1, we plot a binscatter of county weights by population vs. county weights by users in our transaction data.

Another common concern when using transaction data is whether we are able to observe the totality of income and consumption transactions associated with a given user. For this data source, we observe a complete picture of a household's transactions if the household only banks with and uses credit cards from financial institutions that contract with this aggregating service.[4] While this is unlikely to be true for all users, we focus our household-level analysis on a subset of high-quality users where this is more likely to be the case. The data provider ranks the quality of the transaction data based on completeness and account tenure. We focus on a sub-sample of 165,609 users drawn randomly from the top 10% of the sample based on this measure.

2.2 Identifying Cryptocurrency Exchange Transactions

Leveraging the textual descriptions and merchant information that accompany each transaction in our database, we are able to identify transactions that represent deposits to or withdrawals from popular cryptocurrency exchanges. We assemble a list of major crypto exchanges and do substantial manual inspection to identify all variants of text strings that denote a transaction with major exchanges (e.g., 'Coinbase.com debit card purchase' or 'Gemini Trust Co Txfer'). These exchanges include Coinbase, Binance, Gemini, Crypto.com, Kucoin, Cryptohub, Blocket, CEX.io, and Bitstamp. Our focus on crypto exchanges means that we will necessarily underestimate retail crypto wealth, because some investors hold cryptocurrency in private wallets obtained through direct purchases or mining. It is difficult to determine how much retail cryptocurrency is held off-exchange, but Makarov and Schoar (2021) estimate that since 2015, approximately 75% of total Bitcoin transactions have occurred through exchanges. This finding suggests that transactions with retail crypto exchanges are likely to capture the majority of crypto deposits and withdrawals.

While users interact with exchanges using bank transfers, debit cards, and credit cards, the vast majority of transactions are through a checking account, with credit cards making up less than 2% of cryptocurrency exchange transactions. In addition, while we observe both deposits and withdrawals, nearly 90% of transactions with one of these exchanges are deposits, reflecting

[4] We refer to a user in our data as a household, which is accurate if the household has combined financial accounts. However, it is possible that some individuals in our data live in the same household but maintain separate accounts.

the dramatic growth in deposits to these exchanges as crypto investment has gained in popularity across the country. Approximately 90% of the dollar flow of deposits and withdrawals is conducted with Coinbase.[5] Gemini makes up another 5% of dollar flows, while the remaining exchanges make up under 5% of total dollar flows combined.

We do not observe the actual cryptocurrencies that households purchase. However, since the vast majority of crypto transactions in our data occur on the Coinbase exchange, we can gain insight into likely purchase behavior by looking at aggregate asset holdings on Coinbase. Figure 2 shows the asset mix held on Coinbase in 2019 and 2020. The vast majority—around 70%—of assets held on Coinbase are Bitcoins; roughly another 10% of assets are in Ether. Importantly, very little cash (i.e., fiat currency) is held on Coinbase. Together, these data suggest that deposits to (withdrawals from) Coinbase are most likely to represent purchases (sales) of either Bitcoin or Ether. Consequently, we estimate a household's total crypto portfolio value as

$$\begin{aligned} \text{CryptoWealth}_{i,d} &= \text{CryptoWealth}_{i,d-1} \times \frac{\text{CryptoIndex}_{i,d}}{\text{CryptoIndex}_{i,d-1}} + \text{Deposits}_{i,d} - \text{Withdrawals}_{i,d} \\ \text{CryptoWealth}_{i,t} &= \text{CryptoWealth}_{i,d} \mid \max_{d \in t} d \end{aligned} \tag{1}$$

where crypto wealth for household i on day d is equal to the household's wealth on the previous day multiplied by the daily return on a household-specific crypto index ($\text{CryptoIndex}_{i,d}$). This index consists of Bitcoin and Ether weighted by our estimate of the household's asset mix on the prior day.[6] We then add net deposits to crypto exchanges on that day. This calculation assumes that all money deposited to a crypto exchange is used to purchase a basket of Bitcoin and Ether on the same day as the transaction, where we assign weights based on the relative

[5]Coinbase launched in 2012 and is the largest U.S. crypto exchange. As of October 2023, the total value of crypto assets held on Coinbase represented about 10.4% of total global crypto assets, based on Coinbase's 10Q filing and global cryptocurrency market capitalization from coingecko.com.

[6]We obtain daily cryptocurrency prices, volumes, and market caps from CoinGecko.com.

total market capitalization of the coins on that day.[7] We assume all money withdrawn from a crypto exchange is split pro rata across Bitcoin and Ether based on the portfolio weights from the prior day. We further assume that initial crypto wealth is zero and then calculate monthly crypto wealth ($\text{CryptoWealth}_{i,t}$) as the household's portfolio value on the last day of the month t.

The summary statistics for household crypto wealth are reported in Panel A of Table 1. On average, crypto users at the end of our sample have a crypto portfolio worth about $11,010. However, this average is skewed due to a small percentage of users with very large portfolios. The median crypto portfolio is only $464, and the 75$^{\text{th}}$ percentile is $2,840. In contrast, the maximum portfolio is worth about $6 million by 2023 (and the peak portfolio in our sample is $11 million).

The skew in crypto portfolio wealth broadly matches the skew in U.S. household equity holdings. In Appendix Figure A.2, we compare the distribution of crypto wealth in our sample with household equity holdings based on the Federal Reserve's Survey of Consumer Finances (SCF). We see a very similar pattern across crypto and equity holdings—a very small fraction of wealth is held by the bottom 80% of households, and the bulk of equity wealth is split evenly between the 80$^{\text{th}}$–99$^{\text{th}}$ percentiles and the top percentile. This analysis suggests that any differences we observe between consumption out of crypto wealth and equity wealth are not likely to be driven by differences in the distribution of these two types of wealth.

Within our account-level sample, about 16% of households make deposits to retail crypto exchanges at some point between 2014 to 2023. This is very similar to the estimated share of the U.S. population that has traded crypto based on recent survey data.[8] For each household that

[7]Results are robust to basing weights on transaction volume instead of market capitalization or broadening the basket of cryptocurrencies we use to weight holdings (e.g., Internet Appendix Table A.3 vs. Table 3).

[8]Pew Research finds that 16% of the U.S. adults had invested in cryptocurrency in 2021. https://www.pewresearch.org/fact-tank/2021/11/11/16-of-americans-say-they-have-ever-invested-in-traded-or-used-cryptocurrency/.

invests in cryptocurrency, we define average quarterly crypto gains as

$$\text{AvgCryptoGains}_{i,q} = \frac{1}{4} \times \left(\text{CryptoWealth}_{i,q} - \text{CryptoWealth}_{i,q-4} + \text{NetWithdraw}_{i,q-3\rightarrow q}\right), \qquad (2)$$

where Crypto Wealth is calculated as in Equation 1 and $\text{NetWithdraw}_{i,q-3\rightarrow q}$ is defined as a household's total crypto withdrawals less total crypto deposits over the last four quarters, inclusive of the current quarter q. Consequently, Crypto Gains includes both the realized and unrealized gains experienced by the household.

We report the distribution of average quarterly crypto gains in Table 1. Conditional on being a crypto investor, the average quarterly gain in crypto wealth over 2014–2023 is about $146 with a standard deviation of $762. About half of household-quarters experience a quarterly loss. Conditional on a positive gain, the average quarterly gain in crypto wealth is about $365. Conditional on a loss, the average quarterly loss is about $44.

2.3 Other Data

The transaction data provider uses an algorithm to determine the city and state where the household resides. We geocode the county associated with this city using ArcGIS. For the analysis in Section 5, we aggregate cryptocurrency portfolio values to the county-month level. In this analysis, we use a much larger sample of about 6 million households to get a better measure of county-level crypto wealth. We merge these data with the monthly county Zillow Home Value Index (ZHVI). ZHVI is a smoothed, seasonally adjusted house price index that reflects the typical value of a house in the county-month.

2.4 Makeup of Cryptocurrency Investors

Cryptocurrency is a rapidly growing asset class, with a global market value of about \$1.6 trillion as of early 2024. Despite its rapid growth, the decentralized, anonymous nature of blockchain transactions has made it difficult to understand who invests in crypto and what drives this investment decision. In contemporaneous work, Kogan et al. (2023), Chava, Hu, and Paradkar (2022), Divakaruni and Zimmerman (2023), and Hackethal et al. (2022) begin to shed light on these questions. We expand on this work by providing evidence based on actual cryptocurrency transactions for a large, nationally representative set of U.S. households. Because we observe not only crypto transactions, but a complete set of payment transactions, we are the first to be able to characterize investment, income, and consumption patterns of crypto investors.

We more fully describe the characteristics of crypto users in Aiello et al. (2023). Here, we focus on a few key features of the development of retail crypto markets relevant for our later analysis. Figure 3 plots the evolution of deposits to and withdrawals from crypto exchanges. We examine how aggregate crypto deposits and withdrawals, summed across a 10% sample of the 60 million households in our transaction data, correlate with crypto returns (defined based on a market value weighted index of Bitcoin and Ethereum). The four panels of the figure show crypto deposits, withdrawals, new users, and net deposits. The salience of large crypto returns is evident: Both the number of new users and total crypto deposits spike following large run-ups in crypto prices. In fact, the single largest jump in new users occurs in late 2017, following the largest 12-month crypto return in our sample. Interestingly, though, withdrawals also spike around this time, suggesting that at least some households cash out their crypto gains.

An advantage of our transaction data is that we can observe spending patterns for both households that invest in cryptocurrencies and those that do not. In Table 2, we show the average amount of monthly income, spending, and the fraction of spending made up of various categories for crypto investors vs. non-crypto investors. A few key patterns emerge from the data. Crypto adopters have higher incomes than non-adopters: Average monthly income is $7,467 for crypto investors relative to $6,648 for non-investors. Crypto adopters also actively invest substantially more in traditional brokerage accounts.[9]

Despite income differences, overall spending patterns are relatively similar for crypto adopters and non-adopters. The largest differences are in discretionary spending. Consistent with having higher disposable income, crypto investors spend about 1.1 percentage points more of their budgets on entertainment/travel and restaurants than non-crypto investors. Crypto investors also spend substantially less using cash or checks.

Figure 4 shows how the geography of cryptocurrency wealth evolves over time. We aggregate total crypto wealth value to the county level and divide it by the number of households in the county. We then show the county maps at year-end 2015, 2017, 2019, and 2021. In 2015, most coastal counties had wealth of less than $100 per household, while much of the interior of the U.S. had no crypto participation. During the initial run-up in crypto prices in 2017, dozens of counties throughout the U.S. began to accumulate crypto wealth of $1,000 per household or more. By the end of 2021, most populated U.S. counties had crypto wealth of at least $1,000 per household, and some counties had crypto wealth of tens of thousands of dollars per household. The largest per capita crypto values are concentrated in counties located in California, Nevada, and Utah. The geographic variation suggests the possibility that crypto wealth might have differential effects on the local economy across counties, which we investigate in Section 5.

[9]Note that we do not observe pre-tax 401K contributions or similar investments that are withheld from paychecks and thus underestimate the dollar amount of traditional investments made by households.

3 Investment after Growth in Crypto Wealth

The summary stats in Table 2 suggest that crypto users are more likely than non-crypto users to have traditional brokerage investments. Aiello et al. (2023) provide additional evidence that crypto investors are more likely to be sophisticated investors. To the extent that crypto investors are financially sophisticated, we would expect them to rebalance large crypto gains into traditional investments. However, polling data suggests that household crypto investors might view crypto as a substitute for traditional investing. For example, a Pew Research Center Poll in 2022 found that among those respondents who say they have invested in cryptocurrency, 78% say one of their motivations was to have a different way to invest, 54% claim that they think it is easier to invest in crypto than in traditional investments, and 39% say they are more confident in cryptocurrencies than in other investments.[10]

We evaluate the relation between crypto gains and future investment at the household level to shed light on the extent to which crypto users rebalance crypto portfolio gains. In Figure 5, we plot a cross-sectional bin scatter of total brokerage deposits against total cryptocurrency deposits. There is a strong, positive correlation between the two types of deposits. However, for most households the total amount of brokerage deposits is substantially larger than the total amount of crypto deposits. This relation flattens at the high end of crypto deposits. For instance, the average user who deposits $20,000 into cryptocurrency exchanges is observed to invest two to three times as much in traditional brokerage accounts while the average user who invests $50,000 into cryptocurrency exchanges deposits about the same amount in brokerages. This evidence suggests that there are two types of retail crypto investors. For most investors, crypto makes up a small portion of an investment portfolio dominated by traditional brokerage deposits. In

[10]https://www.pewresearch.org/fact-tank/2022/08/23/46-of-americans-who-have-invested-in-cryptocurrency-say-its-done-worse-than-expected/.

contrast, there exist a minority of crypto investors who invest disproportionately in crypto.

To explore this relation in more depth, we examine household investment decisions following crypto gains (and losses) using OLS regressions. The results, reported in Internet Appendix Table A.1, show that there is a small, but significant, momentum effect in retail crypto investing, which is consistent with the trading evidence documented in Kogan et al. (2023). However, we also find evidence that other households re-balance their portfolios; higher crypto gains are associated with crypto withdrawals and with deposits to traditional brokerages.[11]

4 Consumption out of Crypto Wealth

How do increases in crypto wealth affect household consumption? To explore this question, we estimate OLS regressions of the following form:

$$\text{Spending}_{i,q} = \beta\, \text{AvgCryptoGains}_{i,q} + \alpha_i + \delta_{s,q} + \Gamma X_{i,q-1} + \varepsilon_{i,q}. \tag{3}$$

where $\text{Spending}_{i,q}$ represents the total dollars spent by household i over quarter q. We include both household (α_i) and state by quarter ($\delta_{s,q}$) fixed effects as well as controls for lagged income. The regressions include both crypto and non-crypto users; while non-crypto users do not have crypto gains, they form an important control group that helps to estimate trends in consumption behavior. The coefficient β from these regressions can be interpreted as the marginal propensity to consume (MPC) out of a dollar of new crypto wealth.

We report the results from estimating Equation 3 in Table 3. For our main analysis, we exclude the Covid period (years 2020–2021). During Covid, discretionary consumption falls. This drop in

[11]In unreported results, we also find that crypto gains positively predict the absolute value of net crypto withdrawals and that crypto withdrawals positively predict equity deposits.

consumption is particularly large for higher income households (e.g., Chetty, Friedman, Hendren, Stepner, et al., 2020). Because these households are also more likely to have large investment gains, the Covid spending shock leads to negative estimates of the MPC out of both crypto wealth and traditional brokerage wealth (see Internet Appendix Table A.2). The estimated MPC out of crypto wealth during the non-Covid period is large—\$0.11—and highly statistically significant (see column (1)). However, this OLS estimate is biased if realized crypto gains are endogenous to household spending. An investor who anticipates a large expense might choose to liquidate a portion of their portfolio in advance, particularly if the investor believes that crypto prices are likely to fall. Alternatively, an investor might double down on crypto investments in the hopes that a high crypto return will generate the wealth needed to meet the expense. If investor beliefs about crypto returns turn out to be correct, these types of behaviors will lead our OLS estimate to be biased upward, because observed spending will happen to be larger when realized plus unrealized crypto gains are larger.

To alleviate these concerns, we construct an instrument for $\text{AvgCryptoGains}_{i,q}$ using the net returns to crypto over the year multiplied by the household's crypto wealth 4-quarters earlier,

$$\begin{aligned}\text{PassiveGains}_{i,q} = \text{CryptoWealth}_{i,q-4} \times \Bigg[& \left(\frac{\text{BTC}_q}{\text{BTC}_{q-4}} - 1\right) \times \frac{\text{BTCWealth}_{i,q-4}}{\text{CryptoWealth}_{i,q-4}} \\ & + \left(\frac{\text{ETH}_q}{\text{ETH}_{q-4}} - 1\right) \times \frac{1 - \text{BTCWealth}_{i,q-4}}{\text{CryptoWealth}_{i,q-4}}\Bigg], \end{aligned} \tag{4}$$

where BTC_q and ETH_q are the prices of Bitcoin and Ethereum in quarter q, and $\text{BTCWealth}_{i,q-4}$ is the imputed value of the household's Bitcoin portfolio as of one year ago. This instrument can be interpreted as the change in the household's crypto wealth over the prior four quarters caused solely by the performance of the household's initial allocation to crypto. This instrument removes any changes in household crypto wealth that occur due to endogenous portfolio allocation decisions that occur during the year leading up to the spending.

Using passive crypto gains as an instrument for average quarterly gains, we estimate:

$$\text{AvgCryptoGains}_{i,q} = \beta_{FS}\,\text{PassiveGains}_{i,q} + \alpha_i + \delta_{s,q} + \Gamma X_{i,q-1} + \varepsilon_{i,q}. \tag{5}$$

$$\text{Consumption}_{i,q} = \beta_{IV}\,\widehat{\text{AvgCryptoGains}}_{i,q} + \alpha_i + \delta_{s,q} + \Gamma X_{i,q-1} + \varepsilon_{i,q}. \tag{6}$$

Unsurprisingly, passive gains strongly predict actual household crypto gains—the first stage F-statistic is over 11,000 in our main specification. For the instrument to be valid, passive gains in crypto wealth (due to a combination of crypto returns over the prior year and heterogeneity in lagged crypto wealth) must be uncorrelated with any other variable that might affect household consumption, after accounting for year-quarter and household fixed effects.

We report the results from estimating the 2SLS specification from Equation 6 in column (2) of Table 3. We find a positive and highly statistically significant MPC of about $0.09, somewhat smaller than our OLS estimate. The MPC is relatively stable over time. Column (3) shows that although the MPC is moderately larger in the post-Covid period of 2022–2023, the difference is not statistically significant.[12] This MPC out of crypto wealth is around two times larger than estimates of the MPC out of equity wealth, which for individuals at a similar point of the wealth distribution are about $0.04 (Di Maggio, Kermani, and Majlesi, 2020). However, it is much lower than estimates of the MPC out of lottery winnings of about $0.50 (Fagereng, Holm, and Natvik, 2021). One potential explanation for this result is the difference in the distribution of returns across crypto and equity assets. In Appendix Figure A.3, we show that Bitcoin has a much higher volatility than the overall equity market and is more akin to a single volatile stock.

[12] To estimate this regression, we use both passive gains and passive gains multiplied by an indicator for quarters in 2022–2023 as instruments. The F-statistic reported in Table 3 accounts for both instruments. We use an analagous approach to estimate all 2SLS interaction estimates in the paper.

One concern with these estimates is that our imputation of crypto wealth is noisy. In the early years of our sample, the vast majority of investment flows to Bitcoin and Ether. In recent years, however, other coins have grown to play a larger role. For robustness, we re-calculate crypto wealth using a broader weighted index of all coins that have ever made up at least 0.5% of trading volume in 2021, excluding stablecoins, finding very similar results (see Appendix Table A.3).

While our estimates of the MPC out of crypto gains are larger than the estimates the literature finds out of equity wealth, it is possible that this difference is driven by characteristics of crypto investors rather than differences across these asset classes. To rule this out, we need to estimate the MPC out of equity wealth for this sample of crypto investors. To do so, we make two important assumptions: (i) the starting balance of the household's brokerage accounts, and (ii) the composition of their after-tax brokerage investments. These assumptions are more difficult to make for equity wealth than for cryptocurrency wealth, which effectively begins at zero at the beginning of our sample and is dominated by two assets (BTC and ETH). In contrast, after-tax investments probably do not begin at zero in 2014 and they can be spread out across thousands of different assets. With these caveats, we assume that the starting brokerage account balance is zero and that deposits are invested in the S&P 500.[13]

Using these assumptions, we create a proxy for equity wealth using a method analogous to Equation 1. We then estimate the MPC out of imputed equity wealth using a similar 2SLS procedure where we instrument for equity gains using the growth in the S&P 500 multiplied by equity wealth one year ago. Non-crypto investors in our sample have an estimated MPC out of equity wealth of $0.05 (Table 3 column (5)), similar to other estimates in the existing literature.[14] How-

[13]We iteratively adjust the starting balance to be equal to the $|min(0, min(\text{NetBalance}))|$ to reflect a plausible lower bound on the beginning balance.

[14]Estimates of the MPC out of unrealized equity gains range from around 0.03 to 0.10 (Carroll, Otsuka, and Slacalek, 2011; Case, Quigley, and Shiller, 2005; Davis and Palumbo, 2001; Di Maggio, Kermani, and Majlesi, 2020; Dynan and Maki, 2001; Guiso, Paiella, and Visco, 2006).

ever, crypto investors have an MPC out of equity gains of \$0.07 (Table 3 column (4)), nearly 40% higher. These results suggest that part of the higher MPCs out crypto wealth is due to differences in investor type.

We next investigate whether households treat crypto losses differently from gains. We split the sample into household-quarters with an average crypto gain over the past year versus an average crypto loss. We include non-crypto investors in both samples. The results are reported in Table 4. Column (1) shows that the MPC out of crypto gains is about \$0.08. The MPC out of crypto losses, reported in column (2), is similar (\$0.11). We test if the difference in these MPCs is statistically significant by estimating the MPC in the full sample and including an interaction between an indicator for average crypto losses with the level of average quarterly crypto gains. The coefficient on this interaction is positive, but insignificant. Given this finding, we would anticipate meaningful reductions in spending following crypto crashes.

Another dimension in which we might expect heterogeneity in consumption responses is liquidity constraints. In most models of consumption, liquidity or credit constrained households consume more out of an exogenous wealth shock. We split our sample of households into low and high savings subsamples based on their average annual net savings (total income less total spending). We then re-estimate our 2SLS specification separately for each sub-sample in Table 5. Households that on average save relatively little of their income respond much more strongly to crypto gains. These relatively constrained households spend nearly \$0.14 of every dollar of crypto gains. In contrast, the less constrained high savings households only spend about \$0.05 per dollar of crypto gains. These differences are statistically significant at the 10% level (see column (3)). This variation in the consumption response to crypto gains is very similar to the variation in the consumption response to traditional investment gains. In columns (4)–(6) of of Table 5 we show that low savings households consume much more of their equity gains—roughly \$0.10 per dollar—while high savings households have a much smaller MPC of about $0.03.

One difference in consumption responses across crypto and traditional investments is with respect to income. We split households into high and low income based on the sample median in the first quarter that the household enters the data. In columns (1) through (3) of Internet Appendix Table A.4, we find that the MPC out of crypto gains increases in income, although the differences are not statistically significant. In contrast, columns (4) through (6) show that the MPC out of equity gains decreases in income.

The transaction data that we use allows us to categorize consumption. In Internet Appendix Table A.5, we explore how different categories of consumption respond to changes in crypto wealth. The largest effect is in spending by check; this spending represents nearly 50% of the overall MPC.[15] There is also a large increase in spending on general merchandise. Most of the remaining consumption is split evenly entertainment/travel, groceries, and restaurants. Consequently, it looks like households use crypto gains to increase durable spending (most check spending is likely to be on durable goods), as well as to increase discretionary spending.

The results in this section show that households change their consumption behavior following increases in crypto wealth. While the MPC out of crypto wealth is larger than the MPC out of equity wealth, much of this is driven by the fact that crypto investors consume more out of all types of investment gains. Overall, consumption behavior out of crypto wealth looks remarkably similar to consumption behavior out of equity wealth, suggesting that investors treat these assets in broadly similar ways.

[15]The data do not allow us to determine what cash/check expenses are for. Note that cash/check purchases make up about 17–19% of overall household spending, on average (see Table 2).

4.1 Crypto Withdrawals Event Study

The consumption changes documented in the previous section occur following largely unrealized changes in crypto wealth. Spending decisions following large realized gains might follow a different pattern. Of the crypto users in our data, nearly 50% withdraw at least some money from a crypto exchange at some point. The decision to realize crypto gains (i.e., withdraw money from a crypto exchange) is clearly endogenous, and likely driven in part by expected household expenses and balance sheet liquidity. The trends visible in Figure 3 suggest that at least one additional driver of crypto withdrawals is crypto returns. Aiello et al. (2023) examine this relation more formally and find evidence that lagged Bitcoin returns positively predict retail crypto withdrawals.

To evaluate how households' consumption decisions change following large withdrawals from crypto exchanges, we use an event study framework. We estimate:

$$y_{i,t} = \beta\, \mathbb{1}(t > \tau_i) + \alpha_i + \gamma_y + \delta\, \text{Income}_{i,t-1} + \varepsilon_{i,t}, \tag{7}$$

where the dependent variable $y_{i,t}$ represents aggregated spending in various consumption categories for user i in month t. The primary independent variable of interest is an indicator equal to 1 when month t exceeds the event of a large withdrawal τ_i.

We define large withdrawal events to be the first time a household withdraws more than $5,000 of crypto wealth. There are 2,577 such events in our sample with a mean withdrawal size of about $16,500. Appendix Figure A.4 plots the number of big crypto withdrawals over time. There is a huge spike in large withdrawals during the crypto price run-up of 2017, and other noticeable spikes following the large returns in early 2021. Despite this lumpiness, there are large withdrawal events in most months since 2016. We include household fixed effects (α_i) and year fixed effects (γ_y) and control for lagged monthly household income. We restrict the analysis to a window that is 12 months before and after event τ_i. These results establish that crypto wealth is used to finance consumption increases, regardless of whether a crypto withdrawal caused the increase in consumption or the desired increase in consumption caused the draw-down of crypto wealth. If the causal mechanism is expectations driving withdrawals, this also implies to some degree that higher consumption may not have been feasible without this extra liquidity.

Results in Table 6 report the differences in annualized monthly spending across various categories following an individual withdrawing at least $5,000 from a crypto exchange. The coefficient in column (1) indicates that total spending in the year following a large crypto withdrawal increases by $5,754 relative to that household's spending in the prior year. Similar to consumption out of mostly unrealized crypto wealth gains, much of the increased consumption comes from cash and general merchandise. We also see large increases in discretionary spending on entertainment, travel, groceries, and restaurants. Finally, crypto withdrawals are also spent on large durable goods. Auto spending increases by $211, and direct housing expenses–mortgage spending, insurance, and utilities—increase by nearly $770.[16]

Because it appears that many large crypto withdrawals are spent on housing, we focus on mortgage spending to try to understand if there are pre-existing trends that might lead a household to liquidate crypto wealth. We illustrate the event study for mortgages in the top panel of Figure 6 where we plot the coefficient in event time relative to the date of a large withdrawal from a crypto exchange. Mortgage spending is constant in the 6-months leading up to a large crypto withdrawal, but rises significantly beginning 3 months after a withdrawal. In contrast to mortgage spending, rent spending (bottom panel) is constant across the event window.

We next examine how the effect of crypto withdrawals on mortgage spending varies with

[16]While they are less directly tied to housing, the increases in spending by check and on general merchandise could also represent down payments, escrow deposits, and furnishing a new house.

the size of the withdrawal. Table 7 reports results for mortgage expenses following withdrawals larger than $5,000 and for those larger than $10,000. Columns (1) and (2) show that larger crypto withdrawals are followed by even larger increases in mortgage spending. For example, users who withdraw at least $10,000 from crypto exchanges increase their mortgage spending by $597 over the next year, about 20% more than the effect from withdrawing at least $5,000.

This increase in mortgage spending could be driven by new house purchases, but also could represent households prepaying their existing mortgage. In columns (3) and (4) of Table 7, we re-estimate the event study using an indicator for a new homeowner as the outcome variable. We define a monthly indicator equal to one if a household spends more than $2,500 total on mortgage payments in the next six months after spending less than $100 total in the 6 months before the crypto withdrawal. Using this indicator as a proxy for new homeownership, we find that a crypto withdrawal of at least $10,000 increases the probability of transitioning into homeownership by about 8.2 percentage points, or about a 90% increase relative to the sample mean.

In Internet Appendix Table A.6, we find that households also spend more on their monthly mortgage following a withdrawal from a brokerage account, but the effects do not seem to depend on the size of the withdrawal. Households also transition into homeownership after large withdrawals from traditional brokerages, but the rates are roughly half those following crypto withdrawals.

5 Aggregate Impact of Crypto Wealth on Local House Prices

In Section 4.1, we show that households spend more on housing following large withdrawals from crypto exchanges. These individual-level house purchase decisions might put price pressure on local housing markets, particularly since Figure 4 shows that household crypto wealth is geographically concentrated. In this section, we explore the extent to which aggregate changes in crypto wealth affect local housing markets. We first define monthly county-level crypto wealth as

$$\text{CryptoWealth}_{c,t} = \sum_{i \in c} \text{CryptoWealth}_{i,t} \tag{8}$$

where $\text{CryptoWealth}_{i,t}$ is the crypto wealth for household i at the end of month t as defined in Equation 1, and county-level crypto wealth, $\text{CryptoWealth}_{c,t}$, is equal to the sum of end of month crypto wealth for all households living in county c in month t. Unlike our household-level analysis, where we focus on a smaller sample of households, we aggregate county-level crypto wealth over the entire database of user transactions, but filtering to users who are flagged by the data provider as high quality. This procedure results in an underlying sample of approximately 10% of users, or roughly 6 million households.

We then define annual county-level crypto gains per capita as

$$\text{CryptoGains}_{c,t} = \frac{\text{CryptoWealth}_{c,t} - \text{CryptoWealth}_{c,t-12} + \text{NetWithdraw}_{c,t-11 \to t}}{\text{Households}_{c,y-1}}. \tag{9}$$

$\text{NetWithdraw}_{c,t-11 \to t}$ is the sum of crypto withdrawals less deposits in county c over the prior 12 months. Similar to our individual-level measure of crypto gains, $\text{CryptoGains}_{c,t}$ includes both realized and unrealized crypto gains for the county over the prior 12-months. We then scale by the number of households in our data located in the county as of the end of the previous year. Assuming that our transaction data represents a random sample of each county, this scaling results in an unbiased estimate of county-level per capita retail crypto gains.

We investigate the relation between county-level crypto gains and house prices by estimating regression models of the following form:

$$\log \text{ZHVI}_{c,t} = \beta_{OLS} \log \text{CryptoGains}_{c,t} + \phi_s \log \text{ZHVI}_{c,t-1} + \alpha_c + \alpha_t + \varepsilon_{c,t}, \tag{10}$$

where $\text{ZHVI}_{c,t}$ is the monthly county-level Zillow Home Value Index (ZHVI). County (α_c) and year-month (α_t) fixed effects control for differences in the levels of county wealth and for trends in housing prices. We further include the lagged ZHVI to control for local housing market dynamics. Our standard errors are clustered by county and we weight the regressions by the ratio of users in the county to total county population to minimize errors due to sparse sampling.

For β_{OLS} to recover the causal effect of increases in county crypto wealth on house prices, the growth in the county's crypto wealth over the preceding year must be uncorrelated with future housing prices. There are two reasons this is unlikely to be the case. First, Equation 10 potentially suffers from reverse causality—increasing house prices in an area might cause households to sell cryptocurrency to fund a house purchase, reducing the value of the county crypto portfolio. Depending on what happens to crypto prices following this crypto withdrawal, a contemporaneous OLS estimate can be biased in either direction. Second, counties that become wealthier are likely to have rising house prices and could also potentially have larger deposits into crypto. This omitted variable potentially biases our OLS estimate upward.

We address these concerns by exploiting heterogeneity in a county's historical crypto participation to run two natural experiments—a difference-in-differences as well as an instrumental variables approach—that establish the causal effect of crypto wealth on local home prices.

5.1 Difference-in-Differences

We first use a differences-in-differences approach surrounding the large run-up in Bitcoin prices in late 2017. Over the entire year, Bitcoin prices increased from \$954 to \$14,003—a return of nearly 1,400%, and the single largest 12-month return in our sample. Several features of this run-up make it an attractive setting to study the effect of increases in crypto wealth on housing markets.

First, given the massive returns over this period, early investors in Bitcoin experienced a substantial increase in crypto wealth. Second, during this time period crypto investing was dominated by Bitcoin—as of December 2016, Bitcoin made up 87% of all crypto coins based on market cap. This makes our imputed measure of crypto wealth more accurate during this run-up than it is during later time periods when other crypto currencies are more developed. Finally, the run-up in Bitcoin prices also led to large withdrawals from crypto exchanges, and our evidence in Section 4.1 shows that large withdrawals are often spent on housing purchases.

Motivated by this idea, we compare house prices in the months surrounding this run-up-induced crypto withdrawal in counties with high levels of crypto wealth before the price run-up to counties with low levels of crypto wealth. Formally, we estimate

$$\log\ \text{ZHVI}_{c,t} = \beta\, \text{HighCrypto}_{c,2016} \times \text{Post}_t + \phi_s \log\ \text{ZHVI}_{c,t-12} + \alpha_c + \alpha_t + \varepsilon_{c,t}, \qquad (11)$$

where $\text{HighCrypto}_{c,2016}$ is equal to one for counties that have top tercile per capita crypto wealth as of December 2016. We omit counties in the middle tercile of per capita crypto wealth from the sample. Panel (a) of Figure 7 shows the geographic dispersion of high vs. low crypto wealth counties in our sample. Post_t is an indicator variable equal to one for months after the Bitcoin price run-up begins. Panel (b) of Figure 7 shows a marked increase in the growth rate of Bitcoin prices beginning in May 2017; consequently, we define event-month zero of the post-period as of this month. Panel (c) of Figure 7 confirms that high crypto wealth counties are treated by this Bitcoin shock; these counties have a much larger spike in crypto withdrawals during the post-period than low crypto wealth counties.

To examine the assumption of parallel trends in house price growth, in Figure 8 we plot event time coefficients from a difference-in-differences model that interacts the high crypto wealth indicator with indicators for each month around the crypto price shock. We omit event-month $t = -1$. The estimated coefficients on the interactions are small, negative, and not significantly different from zero in the pre-period. In contrast, the coefficients are positive and clearly significant after crypto withdrawals begin.

One important remaining concern is whether there exists any other event that occurs at the same time as the Bitcoin run-up and differentially affects house prices in high and low crypto wealth counties. Given the volatility of Bitcoin, both the timing and magnitude of the run-up can reasonably be thought of as random. However, county concentrations of crypto wealth are not random. Because we focus on historical county crypto wealth, reverse causality is not an issue (i.e., house price growth in 2018 did not cause changes to crypto portfolio values in 2016). However, it is possible that the selection into historical crypto wealth is correlated with other time-varying county characteristics that confound the interpretation of our experiment.

The geographic dispersion of high vs. low crypto wealth counties visible in Panel (a) of Figure 7 suggests one possible concern. While there is substantial variation in crypto wealth in the interior of the country, most of both coasts are made up of high crypto wealth counties. These areas are more wealthy and also have higher levels of equity market participation.[17] If the correlation between equity market returns and crypto returns is high enough, our difference-in-

[17] This conjecture is consistent with the evidence in Section 2.4 suggesting that crypto participation is positively correlated with equity market participation.

differences estimates may reflect the effect of equity wealth rather than crypto wealth.

We take three steps to alleviate concerns that our difference-in-differences experiment might be contaminated by equity returns. First, we compare the pattern of Bitcoin returns with S&P 500 returns in the months surrounding the crypto wealth shock (see Appendix Figure A.5). S&P 500 returns are relatively flat or even falling during the crypto wealth shock. Second, while high crypto wealth counties have a large spike in crypto withdrawals following the Bitcoin run-up, Appendix Figure A.6 shows no discontinuous change in withdrawals from brokerage accounts around this event, suggesting that high crypto wealth counties are not realizing especially large equity gains during the post-period. Finally, we control for county level per capita equity gains over the last year.[18]

We estimate the difference-in-differences specification in Equation 11 and report the results in Table 8. We estimate both the traditional difference-in-differences coefficient using an indicator for high crypto wealth counties (columns (1) and (3)), as well as a continuous version where we interact the post indicator with the log county crypto wealth per capita as of 2016 (columns (2) and (4)).[19] Across both specifications, high crypto wealth counties experience higher house prices in the months after the Bitcoin price run-up relative to low crypto wealth counties.

The estimated effect of crypto wealth on county house prices in column (1) indicates that house prices grow about 43 basis points faster in the post-period in high crypto wealth counties relative to low crypto wealth counties, or roughly 11% of the standard deviation in house price growth over 2018. In dollar terms, the estimate in column (3) indicates that house prices are about $2,005 higher in high crypto wealth counties in the nine months following the Bitcoin price shock. This is about a one percent increase in prices relative to the median county house price.

[18]Results are robust to omitting this control. See Section 5.2 for details on the calculation of county equity gains.

[19]The sample sizes differ across these specifications because we omit the middle tercile of county crypto wealth from the sample when using the high crypto wealth indicator.

The continuous specification implies a similar, but smaller economic magnitude. The estimated elasticity combined with a change in county crypto wealth from the 25$^{\text{th}}$ to the 75$^{\text{th}}$ percentile indicates that house prices increase by about 13 basis points.[20]

5.2 Instrumental Variables Strategy

In this section, we extend the experiment underlying the difference-in-differences analysis to the full time series covering 2015–2023 by using a two-stage least squares (2SLS) specification. We construct an instrument for $\text{CryptoGains}_{c,t}$ in the same spirit of the passive gains instrument we use in our household-level analysis (see Equation 4). Specifically, we instrument for county-level crypto gains using county-level passive gains, calculated by taking the 12-month Bitcoin-Ethereum net return over the year multiplied by the county's crypto wealth 12-months earlier:

$$\begin{aligned}\text{PassiveGains}_{c,t} = \frac{\text{CryptoWealth}_{c,t-12}}{\text{Households}_{c,t-12}} \times \Bigg[\left(\frac{\text{BTC}_t}{\text{BTC}_{t-12}} - 1 \right) \times \frac{\text{BTCWealth}_{c,t-12}}{\text{CryptoWealth}_{c,t-12}} \\ + \left(\frac{\text{ETH}_t}{\text{ETH}_{t-12}} - 1 \right) \times \frac{1 - \text{BTCWealth}_{c,t-12}}{\text{CryptoWealth}_{c,t-12}} \Bigg], \quad (12)\end{aligned}$$

where BTC_t (ETH_t) is the price of Bitcoin (Ether) at the end of month t. This instrument can be interpreted as the change in county crypto assets per capita over the prior 12-months caused solely by the performance of that county's initial allocation to crypto. This instrument deals with reverse causality by using the net dollars the county would have earned on their crypto portfolio had they not deposited or withdrawn any additional funds over the year.

For the instrument to successfully alleviate concerns that broader changes in county wealth may simultaneously drive crypto investment and house prices, passive gains in crypto wealth must be uncorrelated with any other change in non-crypto wealth that might affect house prices,

[20] The 25$^{\text{th}}$ percentile is 1.2 and the 75$^{\text{th}}$ percentile is 3.1, so the elasticity implies an increase of $(\frac{3.1}{1.2})^{0.0014} - 1$.

after accounting for year-month and county fixed effects. This exclusion restriction is likely to be satisfied for many sources of wealth. For example, because the timing of Bitcoin returns is quasi-random, these returns are unlikely to be correlated with growth in wealth due to changes in the county's occupation or industry mix. In addition, we find similar results when we directly control for county per capita income growth to ensure that changes in income do not drive our results.

The most plausible remaining concern is that Bitcoin or Ethereum returns are correlated with equity returns and that county-level heterogeneity in crypto wealth is also correlated with heterogeneity in equity wealth. We take two approaches to alleviate this concern. First, we control for county-level equity gains over the prior 12 months. Using an aggregation mirroring our crypto gains measure, we control for rolling changes in the county equity portfolio over the past 12-months to account for any time varying trends in equity wealth at the county-level.[21] Second, to alleviate concerns about correlation between equity and crypto returns, we construct an alternative instrument measuring excess Bitcoin returns over equity market returns:

$$\begin{aligned}\text{ExcessPassiveGains}_{c,t} = \frac{\text{CryptoWealth}_{c,t-12}}{\text{Households}_{c,t-12}} \times \Bigg[& \frac{\text{BTC}_t}{\text{BTC}_{t-12}} \times \frac{\text{BTCWealth}_{c,t-12}}{\text{CryptoWealth}_{c,t-12}} \\ & + \frac{\text{ETH}_t}{\text{ETH}_{t-12}} \times \frac{1 - \text{BTCWealth}_{c,t-12}}{\text{CryptoWealth}_{c,t-12}} - \frac{\text{SP500}_t}{\text{SP500}_{t-12}} \Bigg]. \end{aligned} \tag{13}$$

Under this definition, our instrument represents the passive excess return of investors' Bitcoin and Ethereum portfolios relative to the return on the S&P 500. This modification results in estimates of the effect of additional crypto wealth in a county relative to how a similar allocation to the equity market would have performed. Controlling for county equity gains and using $\text{ExcessPassiveGains}_{c,t}$ as the instrument yields similar results, suggesting that county variation

[21]We start the portfolio value at zero in 2014, and exclude the first year of data when calculating gains.

in equity wealth does not drive our results.

Using these exogenous crypto gains as an instrument, we estimate:

$$\text{CryptoGains}_{c,t} = \beta_{FS}\,\text{PassiveGains}_{c,t} + \phi\Delta\,\text{ZHVI}_{c,t-3\to t} + \alpha_c + \alpha_t + \varepsilon_{c,t}. \tag{14}$$

$$\Delta\,\text{ZHVI}_{c,t\to t+3} = \beta_{IV}\,\widehat{\text{CryptoGains}}_{c,t} + \phi\Delta\,\text{ZHVI}_{c,t-3\to t} + \alpha_c + \alpha_t + \varepsilon_{c,t}, \tag{15}$$

The returns to initial crypto holdings strongly predict county-level crypto gains—the first stage *F*-statistic is above 1,000 across our main specifications. Table 9 reports the results from estimating the 2SLS specification in Equation 15. We find that growth in county crypto wealth causes county house prices to go up over the next 3 months. The estimates are statistically significant, robust to controlling for equity gains and county income growth, and similar using either the *PassiveGains* or *ExcessPassiveGains* instruments.

Looking across Table 9, the estimates indicate that \$1 of retail crypto wealth gains per person in a county drive house prices up by about \$0.15 over the next three months. These estimates imply that a one standard deviation increase in county per capita retail crypto gains leads to a \$462 dollar increase in county house prices over the next three months. This is about a 27 basis point increase in prices relative to the median, which is a roughly similar magnitude to the estimates obtained in the difference-in-differences analysis.

Together, the evidence in this section and in Section 5.1 show that crypto wealth has a spillover effect on the real economy. Counties that are highly exposed to crypto assets experience faster house price growth following large crypto returns. Given these spillovers, even non-cryptocurrency investors are indirectly affected by changes in crypto wealth.

6 Conclusion

Households in the U.S. have increasingly adopted cryptocurrency as a component of their investment strategy, in part due to the extreme volatility that has led to rapid wealth gains for some investors. This paper is the first to document consumption responses to this newfound crypto wealth and identify spillover effects from this wealth on local house prices. Using financial transaction-level data for millions of U.S. households, we show that household crypto investors appear to treat crypto as one piece of an investment portfolio and use crypto wealth to increase their consumption. The MPC out of crypto wealth is somewhat higher than the MPC out of equity wealth, but much lower than the MPC out of lottery winnings. Overall, consumption behavior following crypto gains is broadly similar to consumption behavior following equity gains. Together, this evidence suggests that for the average household, investing in cryptocurrencies is treated much the same as investing in after-tax brokerage accounts.

Households also withdraw crypto gains to purchase housing—both to enter the market as new buyers and to upgrade their existing housing. This increased spending on housing puts upward pressure on local house prices, particularly in areas that are heavily exposed to crypto assets. In the aggregate, growth in county-level crypto wealth causes county house prices to increase.

According to cryptocurrency advocates, crypto returns have been mostly uncorrelated with other asset classes. Furthermore, recent crashes in cryptocurrency markets have appeared to have limited contagion effects on broader financial markets. While crypto may have limited spillover effects onto other financial assets, our results show that crypto investment does affect real assets. As a result, the distribution of crypto wealth has meaningful implications for the real economy.

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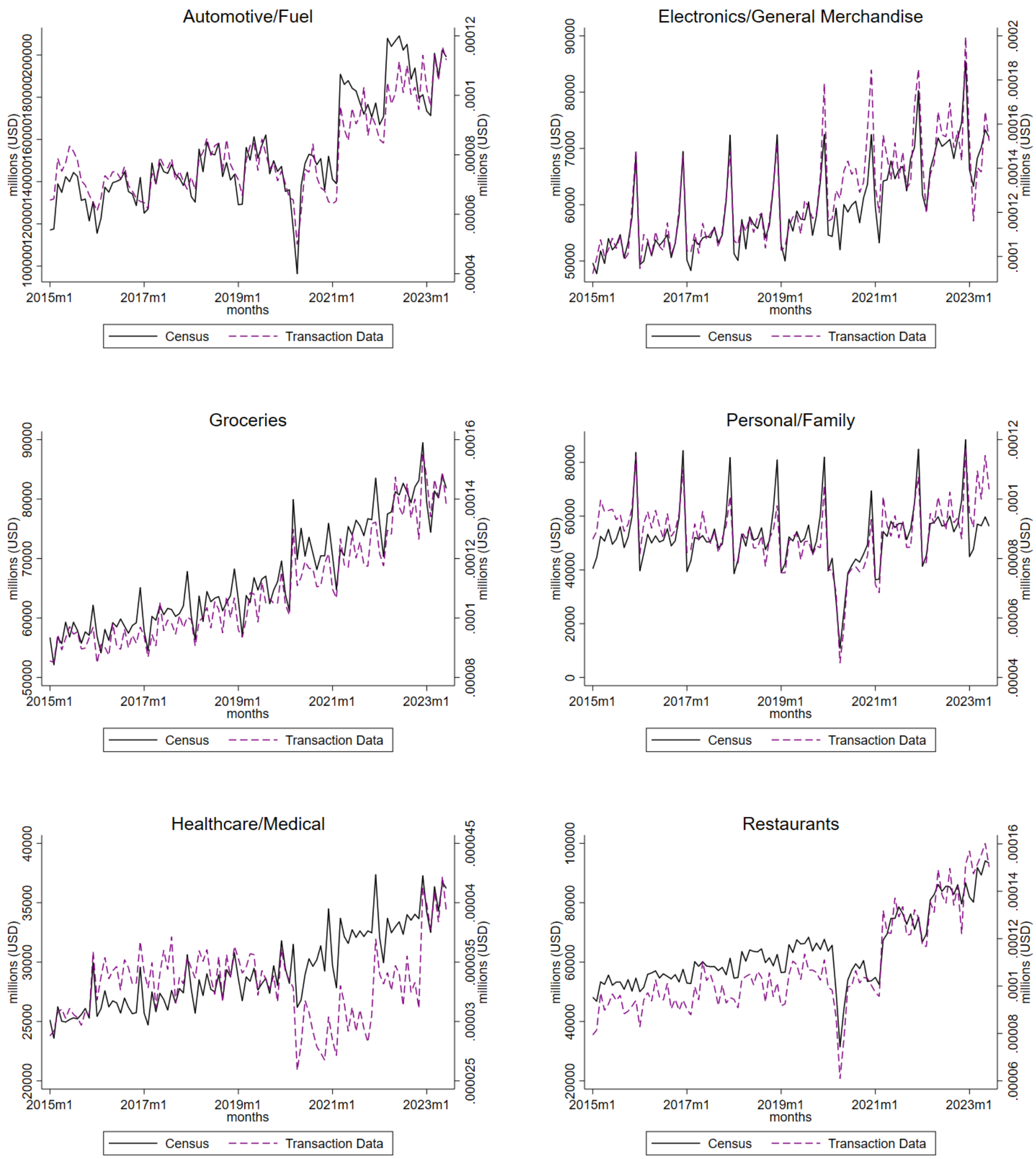


Figure 1. Spending in Data vs. Census Retail Sales. Each panel displays two monthly series from January 2015–June 2023. The solid line displays total sales in the specified category from the Census Retail Sales. The dotted line displays spending per user in the specified category as observed in the data from the large transaction aggregator.

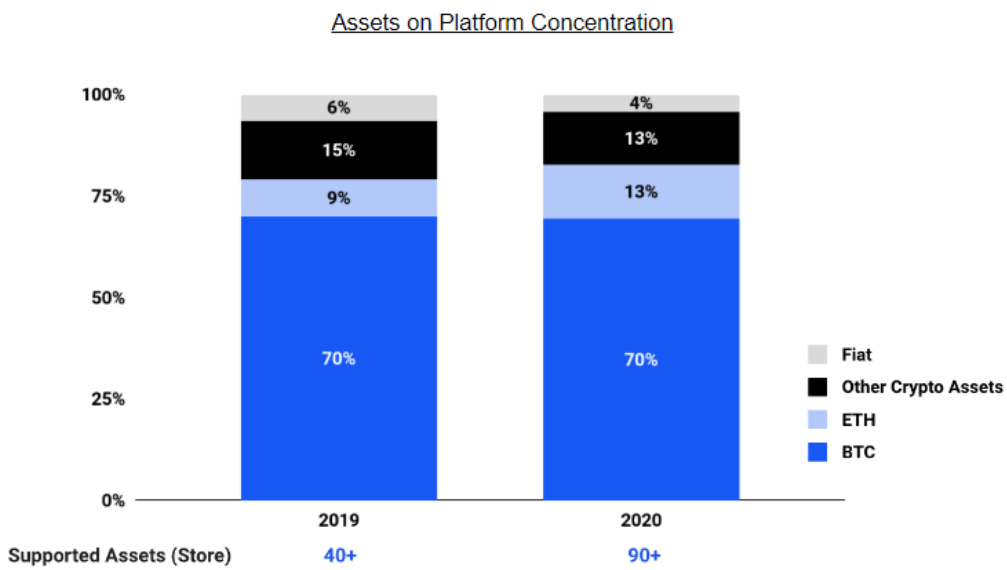


Figure 2. Cryptocurrency Assets Held through Coinbase. This figure shows the percentage of various cryptocurrencies held on Coinbase in 2019 and 2020. Source: Coinbase S-1 filed on March 23, 2021.

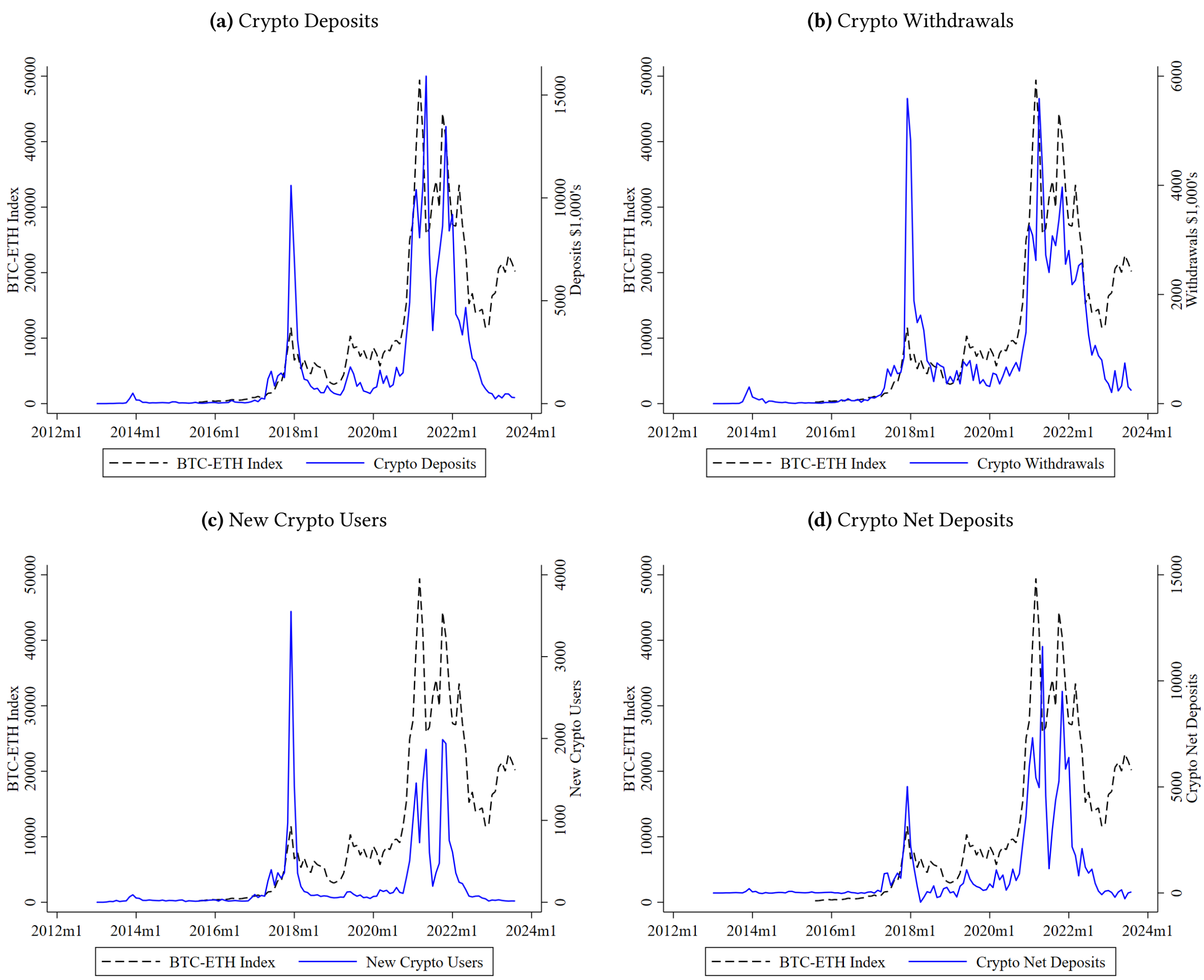


Figure 3. Crypto Adoption and Crypto Portfolio Activity. This figure shows the relation between retail crypto activity (solid line) and a value-weighted Bitcoin-Ethereum index (dashed-line). Figure (a) depicts flows of deposits into cryptocurrencies. Figure (b) shows withdrawals or redemption of crypto. Figure (c) shows the number of new crypto users in the month, where a new user is defined by the first deposit into crypto greater than $5. Finally, Figure (d) shows the net deposits into crypto which is the total deposits minus withdrawals.

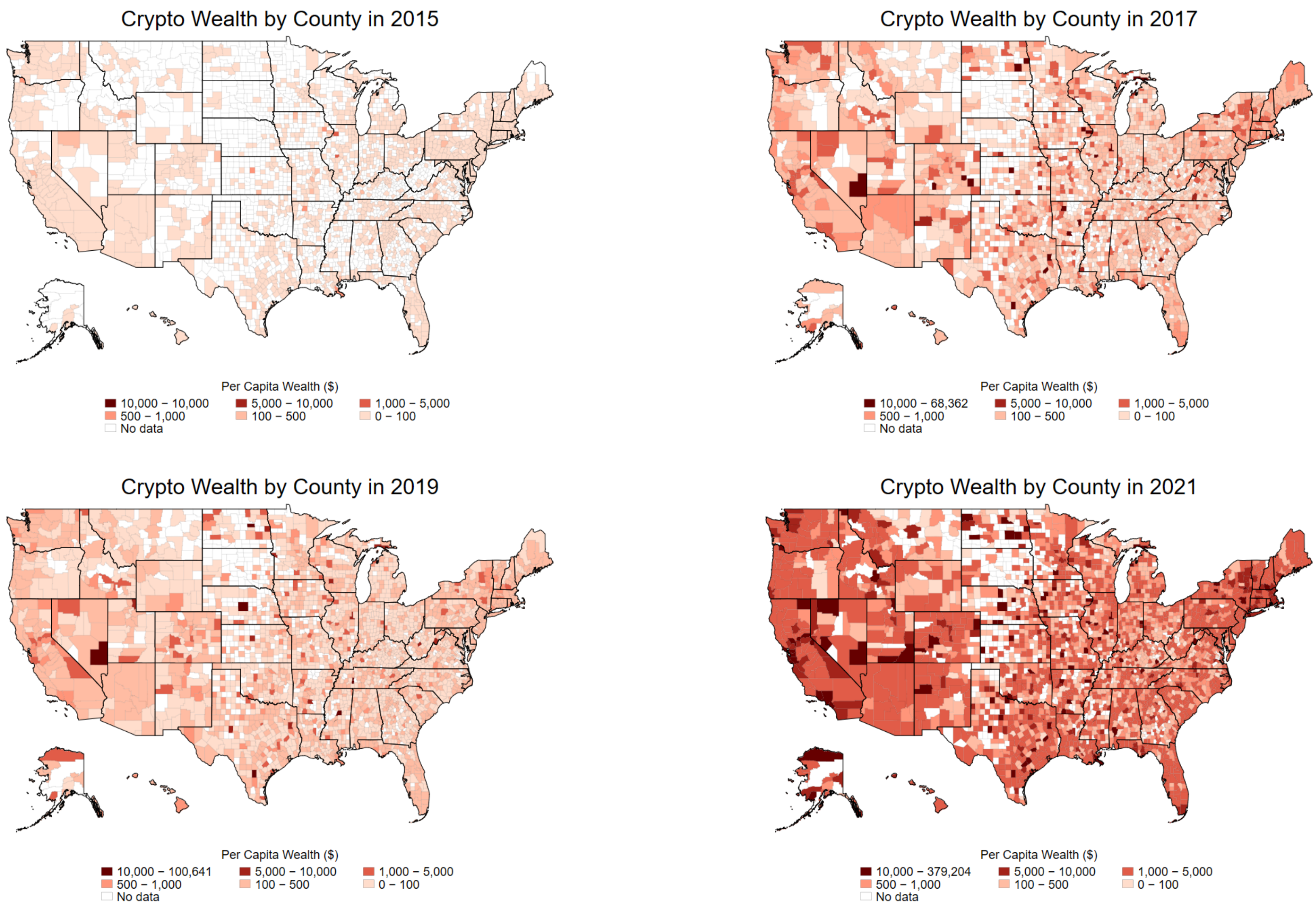


Figure 4. Crypto User Geography over Time. This figure shows the geographic evolution of crypto activity over time. We identify transactions to cryptocurrency exchanges and assume that deposits and withdrawals represent either buying or selling into a value-weighted Bitcoin-Ethereum index at that day's price. We then aggregate these transactions to calculate the total crypto wealth at the county level. The four panels show snapshots of county-level crypto wealth per capita in December 2015, 2017, 2019, and 2021.

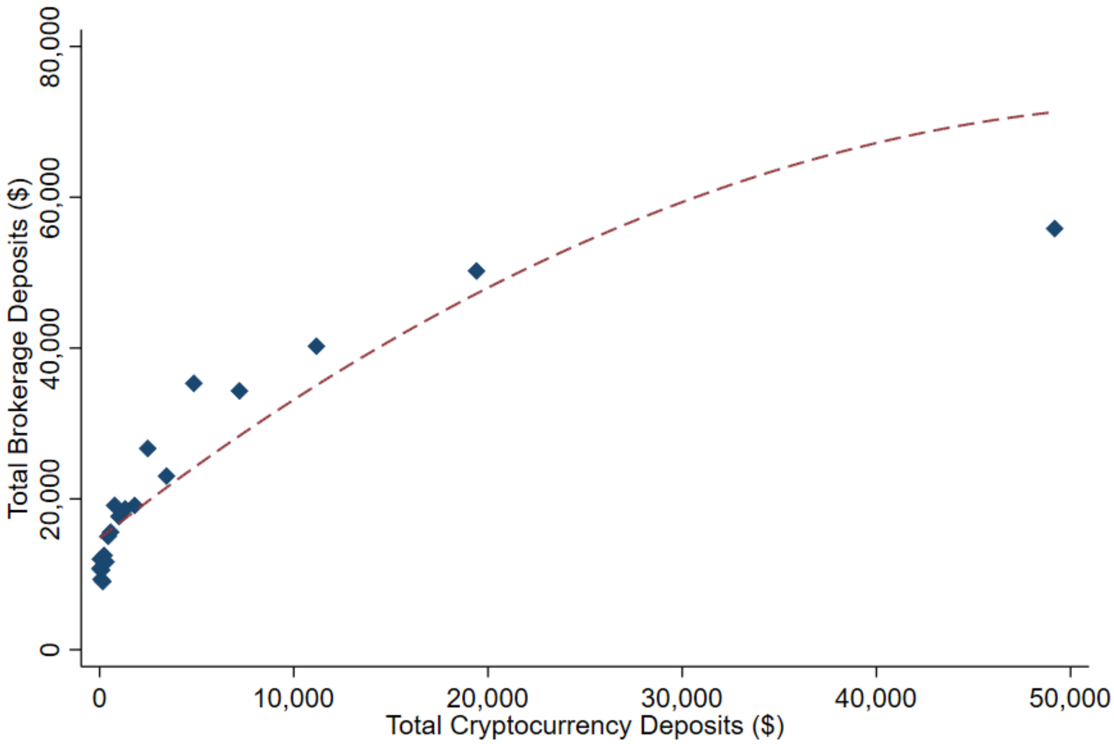


Figure 5. Cryptocurrency Deposits and Equity Investments. This figure depicts a cross-sectional bin-scatter plot with a quadratic fitted line of total deposits to brokerages against total cryptocurrency exchange deposits. Underlying data are at a user level. We limit the plot to users who have cumulatively deposited less than $100,000 to crypto exchanges for ease of exposition due to outliers.

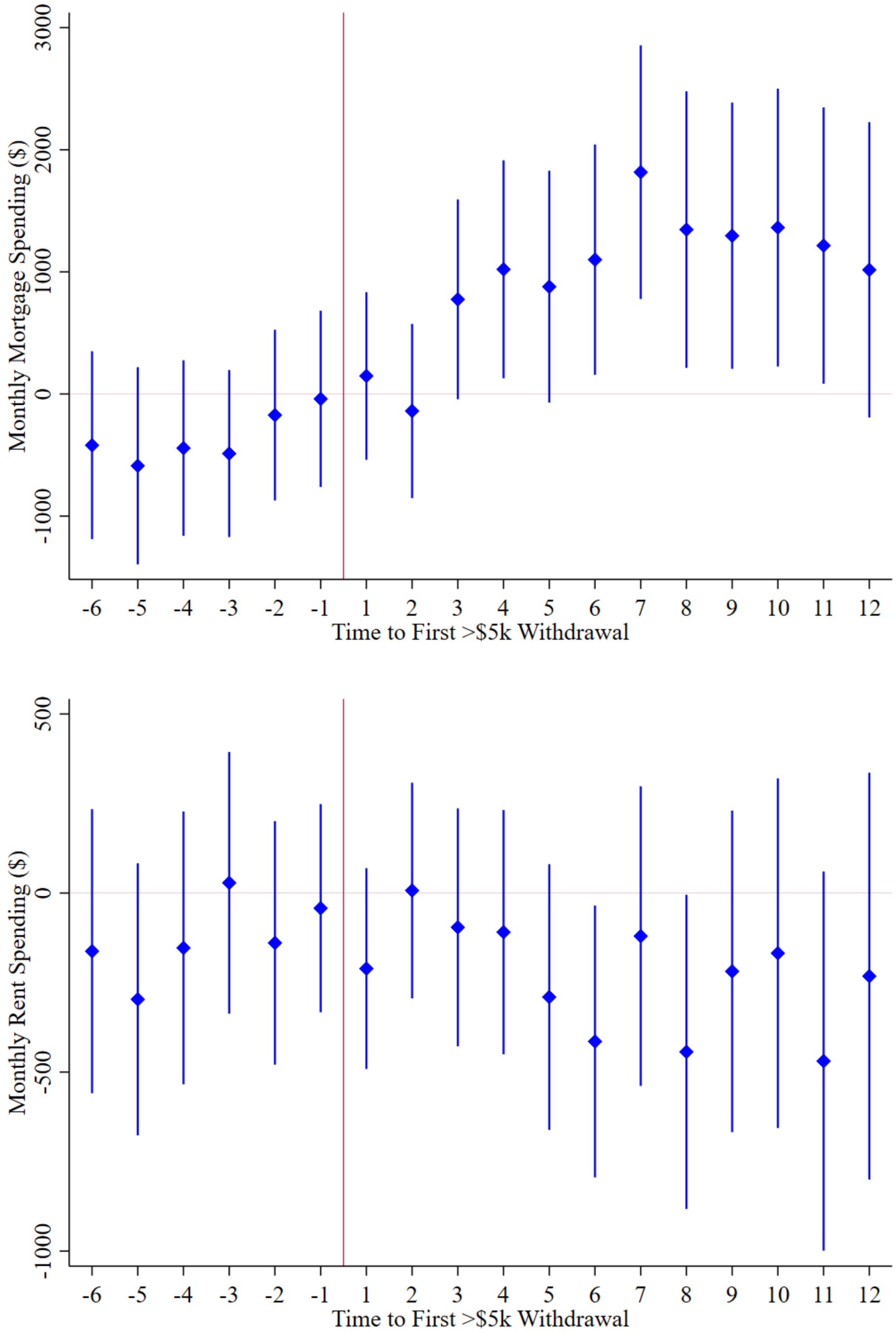


Figure 6. Monthly Mortgage and Rent Spending around First Large Bitcoin Withdrawal. Each panel plots the coefficients on an event-study regression for the months before and after a user first withdraws at least $5,000 from a cryptocurrency exchange. The top panel shows monthly mortgage spending around this event, while the bottom panel shows spending on monthly rent.

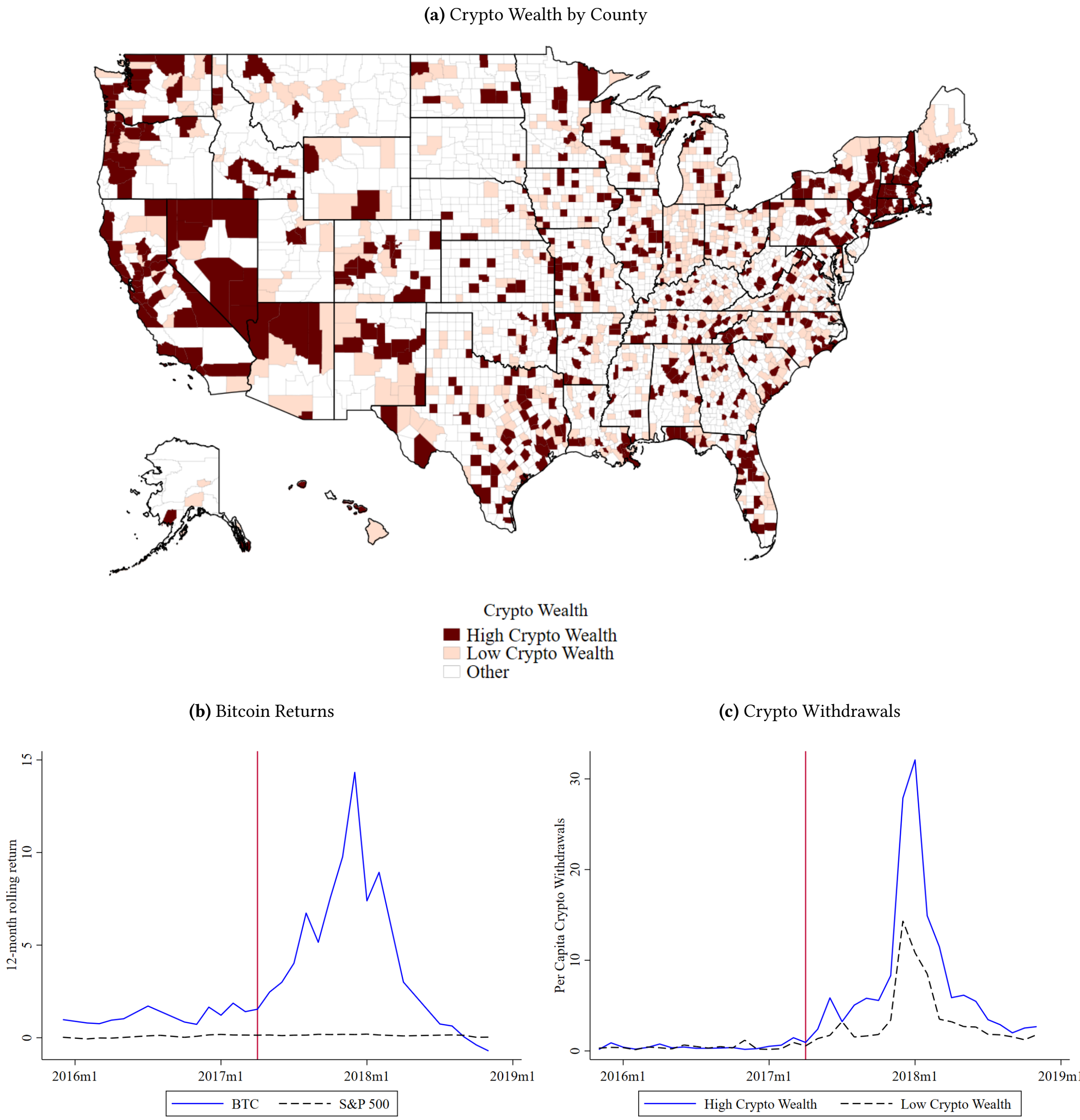


Figure 7. Crypto County Wealth and Withdrawals during the Bitcoin Run-up. The map in Panel (a) highlights counties that have per capita crypto wealth in the top tercile (dark red) and bottom tercile (light pink) as of December 2016; these are the treated and control counties in our difference-in-difference analysis. Panel (b) shows Bitcoin's year over year return in the months surrounding the price run-up. The timing of our treatment is determined by the trend break in Bitcoin returns; the vertical line separates the sample into pre- and post-treatment periods. Panel (c) shows average per capita crypto withdrawals separately for counties with high (top tercile) and low (bottom tercile) crypto wealth as of December 2016.

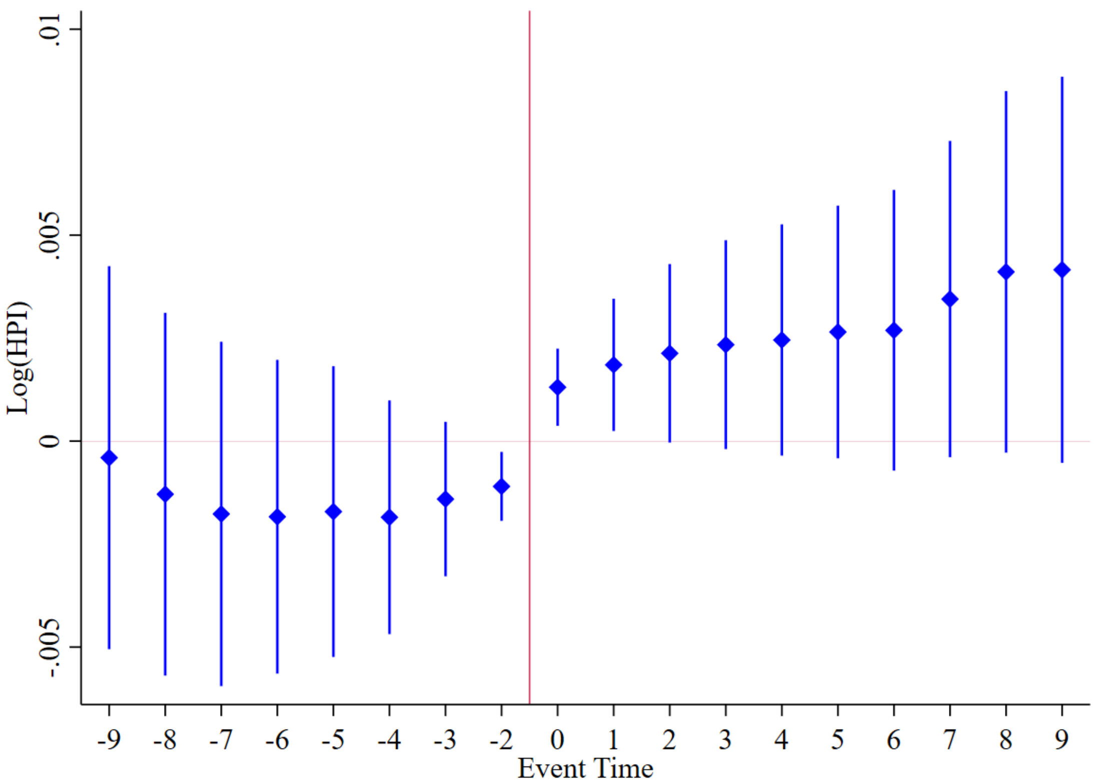


Figure 8. The Bitcoin Run-Up Diff-in-Diff. This figure shows our difference-in-differences analysis of the aggregate effect of county-level crypto wealth on county-level house prices in event time. The y-axis is Log(Median County House Price). Treated (control) counties are defined as counties that are in the top (bottom) tercile of crypto wealth per capita as of December 2016 (see Figure 7). The treatment is defined as the unusually large run-up in Bitcoin prices beginning in May 2017; the vertical line is drawn at month t=-1 in event time, which we set as the baseline (omitted) category.

Table 1

Summary Statistics

This table reports summary statistics for the main variables used in the paper. Panel A reports descriptive statistics for the sample of households used in our MPC analysis in Tables 3–5. This panel is made up of quarterly data from 2015 to 2023 and includes both crypto adopters and non-crypto adopters. Panel B summarizes the sample used in the crypto withdrawal event study in Tables 6 and 7. This sample is limited to crypto adopters who withdraw more than $5,000 of crypto in a single month. We limit the sample to the 24-months surrounding the first such withdrawal. These withdrawal events span the entire sample from 2014–2023. Panel C summarizes the county-level sample used in our difference-in-differences analysis in Table 8, which includes the 18 months surrounding the Bitcoin run-up in 2017. Panel D shows summary statistics for the county-level sample used in our 2SLS analysis in Table 9. This sample is estimated over the full sample from 2015–2023.

Variable	Obs.	Mean	Std. Dev.	Q5	Q25	Q50	Q75	Q95
Panel A: MPC Household-level Sample								
Total Quarterly Spending	165,609	14,391	11,887	3,689	6,909	11,209	17,969	35,314
Total Quarterly Income	165,609	19,699	14,181	4,492	9,219	15,832	26,113	48,615
Conditional on Crypto User								
Avg. Quarterly Crypto Gains	26,622	146	762	-122	-9	-0	18	795
Crypto Exit	26,622	0.098	0.298	0	0	0	0	1
In Final User Period								
Crypto Wealth	26,622	11,010	88,110	0	74	464	2,840	34,191
Cumulative Crypto Deposits	26,622	6,212	14,831	25	200	922	4,221	34,074
Cumulative Crypto Withdrawals	26,622	3,614	32,396	0	0	0	600	12,725
Panel B: Household-level Withdrawal Event Sample								
Total Monthly Spending, Annualized	38,471	79,664	82,505	-36,253	29,529	57,294	102,126	879,676
Lagged Monthly Income	38,471	10,617	8,383	0	4,667	8,393	14,466	40,751
New Homeowner Indicator	38,471	0.092	0.290	0	0	0	0	1
Crypto Withdrawal >$5,000	2,577	16,507	23,119	5,000	6,782	9,851	16,464	340,277
Panel C: County-level Diff-in-Diff Sample								
Median County House Price	27,747	188,325	122,492	80,988	117,536	157,217	218,831	393,308
Log(Median County House Price)	27,747	12.0	0.5	11.3	11.7	12.0	12.3	12.9
Annual House Price Growth	27,747	4.4	3.9	-1.8	2.1	4.3	6.8	10.7
Log(County Crypto Wealth per capita, Dec. 2016)	27,747	2.2	1.4	0.0	1.2	2.2	3.1	4.7
Panel D: County-level 2SLS Sample								
Median County House Price	179,681	205,782	141,456	82,237	123,790	168,928	241,487	445,545
3-month Change in Median County House Prices	179,681	4,058	6,958	-1,810	1,072	2,777	5,499	14,402
Annual per capita County Crypto Gains	179,681	199	3,144	-922	-17	20	164	1,520
Annual per capita County Equity Gains	169,499	2,246	2,300	-37	1,096	1,871	3,206	5,391

Table 2
Summary Statistics of Sample and Crypto Users

This table shows average monthly income and spending for cryptocurrency users and non-cryptocurrency users and the difference between the two. Data are based on a user-level panel of monthly transaction data from 2014 to 2023. ***, **, and * indicate statistical significance in the difference in means at the 1%, 5%, and 10% levels, respectively.

Variable	Crypto Users	Non-Crypto Users	Difference
Total Income	7,467	6,648	819***
Total Spending	4,979	4,738	241***
Traditional Investment	260	152	107***
Crypto Investment	74	0	74***
Crypto Gains	61	0	61***
Percent of Spending:			
AutoFuel	5.2	4.8	0.4***
Cable/Telecom	-10.2	-10.3	0.1
Cash/Check	16.8	19.4	-2.7***
Charity	0.4	0.5	-0.2
Education	0.2	0.6	-0.4
Entertainment/Travel	7.6	6.5	1.1***
Gen. Merch.	21.1	21.1	-0.1
Groceries	9.2	9.4	-0.2***
Insurance	4.9	5.5	-0.6***
Medical	1.9	2.1	-0.2***
Mortgage	8.8	8.2	0.7***
Rent	2.3	1.8	0.5***
Restaurants	10.2	9.1	1.0***
Utilities	3.7	3.9	-0.2***

Table 3
Crypto Gains and Total Spending

This table shows the marginal propensity to consume (MPC) out of crypto wealth. The dependent variable is the household's total spending in the quarter. The sample covers years 2015–2023, but we omit all observations that occur during the Covid period, defined as 2020–2021. *Avg. Quarterly Crypto Gains* is the average quarterly change in the household's crypto wealth over the prior year defined in Equation 2. *Post-Covid* is an indicator equal to 1 for observations in 2022 or 2023. *Avg. Quarterly Investment Gains* is the average quarterly change in the household's traditional brokerage account wealth over the prior year, calculated analogously to Equation 2. All regressions include a control for the household's income from the previous quarter, as well as household and state-by-quarter fixed effects. Columns (1)–(3) are estimated using the full sample of crypto investors and non-crypto investors; crypto gains are equal to zero for non-crypto investors.. Column (4) shows the estimated MPC out of traditional investment gains for the subsample of crypto investors, and column (5) shows this MPC for the subsample of non-crypto investors. In both cases, investment gains are equal to zero for households that do not make traditional brokerage investments. Columns (2) and (3) are estimated using two-stage least squares (2SLS) where passive crypto gains, defined in Equation 4, are used as an instrument for crypto gains. In column (3), we instrument for the interaction of crypto gains with the post-Covid indicator using the interaction of passive crypto gains and the post-Covid indicator. Columns (4) and (5) are estimated using two-stage least squares (2SLS) where passive investment gains, defined analogously to Equation 4, are used as an instrument for investment gains. Passive gains are calculated as what the household would have received if their crypto portfolio (or traditional portfolio) had been fixed 12 months prior and had experienced the value-weighted returns of Bitcoin and Ethereum (or S&P 500 with respect to passive investment gains). The Kleibergen-Paap rk Wald F statistic is reported for all 2SLS specifications. t-statistics in parentheses are heteroskedasticity-robust and clustered at the household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Total Quarterly Spending				
	OLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)
Avg. Quarterly Crypto Gains	0.114***	0.0879***	0.0729***		
	(5.97)	(4.43)	(3.08)		
Avg. Quarterly Crypto Gains × Post-Covid Indicator			0.0325		
			(0.79)		
Avg. Quarterly Investment Gains				0.0678***	0.0487***
				(2.95)	(4.45)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
State × Quarter FE	X	X	X	X	X
Sample	All Households	All Households	All Households	Crypto Investors	Non-Crypto Investors
Observations	3,274,658	3,274,658	3,274,658	569,102	2,705,537
Adjusted R^2	0.692	0.082	0.082	0.081	0.081
Weak ID KP F Stat		11,526	3,383	2,847	9,543

Table 4

Crypto Gains vs. Crypto Losses

This table estimates the MPC out of crypto gains and compares it to the MPC out of crypto losses. The dependent variable is the household's total spending in the quarter. *Avg. Quarterly Crypto Gains* is the average quarterly change in the household's crypto wealth over the prior year defined in Equation 2. The sample includes both crypto investors and non-crypto investors excluding the Covid period (i.e., years 2020 and 2021); crypto gains are equal to zero for non-crypto investors. All regressions include a control for the household's income from the previous quarter, as well as household and state-by-quarter fixed effects. The regressions are estimated using two-stage least squares (2SLS) where passive crypto gains, defined in Equation 4, are used as an instrument for crypto gains. Passive gains are calculated as what the household would have received if their portfolio had been fixed 12 months prior and had experienced the value-weighted returns of Bitcoin and Ethereum. Column (1) presents estimates of the MPC for the subsample of observations with crypto gains ≥ 0, while Column (2) shows estimates for the subsample of observations with crypto gains ≤ 0. To test whether the MPC differs across positive and negative gains, in Column (3) we include all observations and interact crypto gains with an indicator equal to 1 if the average quarterly gain in the last year is less than zero (*Negative Gains*). We instrument for this interaction with the interaction of passive crypto gains and the negative gains indicator. The Kleibergen-Paap rk Wald F statistic is reported for all 2SLS specifications. t-statistics in parentheses are heteroskedasticity-robust and clustered at the household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Total Quarterly Spending		
	2SLS	2SLS	2SLS
	(1)	(2)	(3)
Avg. Quarterly Crypto Gains	0.084**	0.114***	0.0587*
	(2.25)	(2.81)	(1.76)
Avg. Quarterly Crypto Gains × Negative Gains Indicator			0.0575
			(0.98)
Lagged Income Control	X	X	X
Household FE	X	X	X
State × Quarter FE	X	X	X
Sample	Crypto Gains	Crypto Losses	Full Sample
Observations	3,170,985	3,209,457	3,274,658
Adjusted R^2	0.080	0.082	0.082
Weak ID KP F Stat	3,122	60,527	2,556

Table 5

MPC Split by Net Savings

This table shows consumption sensitivity to crypto and equity wealth by split by levels of net savings. The dependent variable is the household's total spending in the quarter. *Avg. Quarterly Crypto Gains* is the average quarterly change in the household's crypto wealth over the prior year defined in Equation 2. *Avg. Quarterly Investment Gains* is the average quarterly change in the household's traditional brokerage account wealth over the prior year, calculated analogously to Equation 2. The sample includes both crypto investors and non-crypto investors excluding the Covid period (i.e., years 2020 and 2021); crypto gains are equal to zero for non-crypto investors. All regressions include a control for the household's income from the previous quarter, as well as household and state-by-quarter fixed effects. The regressions are estimated using two-stage least squares (2SLS) where passive crypto gains, defined in Equation 4, are used as an instrument for crypto gains in columns (1)–(3), and passive investment gains, defined analogously, are used as an instrument for investment gains in columns (4)–(6). Passive gains are calculated as what the household would have received if their crypto (traditional) portfolio had been fixed 12 months prior and had experienced the value-weighted returns of Bitcoin and Ethereum (S&P 500). Households are assigned to high or low net savings subsamples based on whether their average annual net savings (total income less total spending) is above or below the sample median. Columns (1) and (4) are limited to the subsample of below median net savings households and columns (2) and (5) are limited to the subsample of above median net savings households. Columns (3) and (6) use the full sample of households and show the interaction of crypto (traditional) gains with an indicator equal to one for households in the above median net savings subsample. We instrument for these interactions using the relevant measure of passive gains interacted with the high net savings indicator. The Kleibergen-Paap rk Wald F statistic is reported for all 2SLS specifications. t-statistics in parentheses are heteroskedasticity-robust and clustered at the household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Total Quarterly Spending			Total Quarterly Spending		
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Quarterly Crypto Gains	0.139***	0.0494**	0.141***			
	(3.12)	(2.39)	(3.15)			
Avg. Quarterly Crypto Gains × High Savings			-0.0896*			
			(-1.83)			
Avg. Quarterly Investment Gains				0.101***	0.0287***	0.103***
				(4.40)	(2.90)	(4.45)
Avg. Quarterly Investment Gains × High Savings						-0.0747***
						(-2.97)
Lagged Income Control	X	X	X	X	X	X
Household FE	X	X	X	X	X	X
State × Quarter FE	X	X	X	X	X	X
Sample	Low Savings	High Savings	All Households	Low Savings	High Savings	All Households
Observations	1,627,832	1,646,815	3,274,647	1,627,832	1,646,815	3,274,647
Adjusted R^2	0.101	0.072	0.082	0.101	0.072	0.082
Weak ID KP F Stat	3,601	8,094	1,801	2,401	11,850	1,200

Table 6

Crypto Withdrawals and Expenditures

This table presents event study regressions at the household-month level for a sample of crypto investors. The event is defined as the first time a household withdraws at least $5,000 in a single month from a crypto exchange. These withdrawal events span the entire sample from 2014–2023, as shown in Appendix Figure A.4. We include the 25 months surrounding this withdrawal event. *Post First Crypto Withdrawal >$5,000* is an indicator variable equal to one for the 12-months following the withdrawal. We examine changes in consumption following the event for a variety of consumption categories. All regressions include a control for the household's income from the previous month, as well as household and year fixed effects. *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Monthly Spending, Annualized				
	Total Spending	Auto	Cable/Telecom	Cash/Check	Charity
	OLS	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)	(5)
Post First Crypto Withdrawal >$5,000	5753.7***	211.4**	-56.95	1833.9*	11.75
	(4.68)	(2.50)	(-1.40)	(1.85)	(0.36)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	38,471	38,471	38,471	38,471	38,471
Adjusted R^2	0.523	0.305	0.587	0.307	0.571

	Monthly Spending, Annualized				
	Education	Entertain/Travel	General Merch.	Groceries	Insurance
	OLS	OLS	OLS	OLS	OLS
	(6)	(7)	(8)	(9)	(10)
Post First Crypto Withdrawal >$5,000	-54.46	395.4**	2105.7***	177.9**	173.4**
	(-0.32)	(2.56)	(6.82)	(2.22)	(2.21)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	38,471	38,471	38,471	38,471	38,471
Adjusted R^2	0.213	0.392	0.491	0.637	0.480

	Monthly Spending, Annualized				
	Medical	Mortgage	Rent	Restaurants	Utilities
	OLS	OLS	OLS	OLS	OLS
	(11)	(12)	(13)	(14)	(15)
Post First Crypto Withdrawal >$5,000	32.00	500.7**	-64.94	395.3***	92.67*
	(0.64)	(2.27)	(-0.61)	(3.81)	(1.71)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
Year FE	X	X	X	X	X
Observations	38,471	38,471	38,471	38,471	38,471
Adjusted R^2	0.336	0.714	0.544	0.557	0.536

Table 7

Crypto Withdrawals and Transition into Homeownership

This table presents event study regressions similar to those of Table 6 but focusing on mortgage spending and new home ownership. Columns (1) and (3) define a withdrawal event as the first time a household withdraws at least $5,000 in a month from a crypto exchange and columns (2) and (4) define an event as a first withdrawal in excess of $10,000. The dependent variable in Columns (1) and (2) is monthly mortgage spending. In Columns (3) and (4), *New Homeowner* is an indicator variable equal to 1 if the household has had mortgage spending less than $100 over the previous 6 months and more than $2,500 over then following 6 months. All regressions include a control for the household's income from the previous month, as well as household and year fixed effects. *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Monthly Mortgage Spending, Annualized		New Homeowner	
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Post First Crypto Withdrawal >$5,000	500.7**		0.0477***	
	(2.27)		(5.98)	
Post First Crypto Withdrawal >$10,000		597.2**		0.0820***
		(2.01)		(6.87)
Lagged Income Control	X	X	X	X
Household FE	X	X	X	X
Year FE	X	X	X	X
Observations	38,471	20,177	38,476	20,180
Adjusted R^2	0.714	0.715	0.243	0.261

Table 8
Bitcoin Run-Up Diff-in-Diff: County-Month Housing Prices

This table presents difference-in-differences estimates from Equation 11 of the effect of Bitcoin price appreciation on house prices. Observations are at a county-month level; the dependent variable in columns (1) and (2) is the natural logarithm of the monthly Zillow county house price index, while the dependent variable in columns (3) and (4) is the level of the Zillow county house price index. The treatment is defined as the largest rolling 12-month return Bitcoin has ever experienced, which happened at the end of 2017. *Post Run-up* is an indicator for months after April 2017, when the run-up in Bitcoin prices began (see Figure 7). The sample is limited to the 9 months before and after May 2017. Columns (1) and (3) define treated counties as the top tercile of crypto per capita wealth as of December 2016 (*High Crypto Wealth County*); we omit middle tercile counties from these columns. Columns (2) and (4) use the natural logarithm of county-level crypto per capita wealth as of December 2016 (*Log County Crypto Wealth*) as a continuous measure of the degree to which a county is treated. All specifications include a control for log (columns (1)–(2)) or level (columns (3)–(4)) county house prices 1-year prior, *Per Capita Equity Gains* which is the 12 month change in imputed equity value per capita in the county, as well as county and year-month fixed effects. t-statistics in parentheses are heteroskedasticity-robust and clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	County-Month Log Median House Price		County-Month Median House Price	
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
High Crypto Wealth County × Post Run-up	0.00426**		2005.3***	
	(2.44)		(3.49)	
Log County Crypto Wealth × Post Run-up		0.00138**		772.5***
		(2.18)		(3.43)
Per Capita Equity Gains	X	X	X	X
12-Month Lagged Outcome	X	X	X	X
County FE	X	X	X	X
Year-Month FE	X	X	X	X
Observations	18,072	27,747	18,072	27,747
Adjusted R^2	0.333	0.267	0.466	0.521

Table 9

Effect of Crypto Gains on Housing Prices

This table presents of the effect of county-level crypto gains on county house prices. Column (1) presents the results from an OLS estimate, while columns (2)–(4) show the results from instrumental variables estimates where we instrument for county-level per capita crypto gains using *Passive Gains*, defined as the county-level per capita crypto wealth as of 12-months prior to the focal observation multiplied by the focal observation's previous 12-month value-weighted Bitcoin and Ethereum net return (see Equation 12). In column (5), we instrument using *Excess Passive Gains*, defined as the county-level per capita crypto wealth as of 12-months prior to the focal observation multiplied by the focal observation's previous 12-month excess crypto return (i.e., value-weighted Bitcoin and Ethereum return adjusted for market returns as in Equation 13). Observations are at the county-month level starting in 2015 and ending in 2023. All specifications include a control for the change in county house prices over the prior quarter, as well as county and year-month fixed effects. In columns (3)-(5), we control for the 12 month change in imputed equity value per capita in the county (*Per Capita Equity Gains*). In columns (4) and (5), we further control for per capita income growth in the county. The Kleibergen-Paap rk Wald F statistic is reported for all 2SLS specifications. t-statistics in parentheses are heteroskedasticity-robust and clustered at the county level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Change in House Price Index, Next 3 Months				
	OLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)
Per Capita Crypto Gains, Prior 12-Months	0.194***	0.192**	0.156**	0.162**	0.147**
	(2.72)	(2.39)	(2.17)	(2.15)	(2.17)
Per Capita Equity Gains, Prior 12-Months			0.511	0.481	0.491
			(1.33)	(1.31)	(1.31)
Δ House Price Index, Prior 3-Months	X	X	X	X	X
Income Growth, Per Capita				X	X
Year-Month FE	X	X	X	X	X
County FE	X	X	X	X	X
Instrumental Variable		Passive Gains	Passive Gains	Passive Gains	Excess Passive Gains
Observations	179,681	179,681	179,681	169,499	169,499
Adjusted R^2	0.293				
Weak ID KP F Stat		1,276	1,215	1,130	633

Internet Appendix

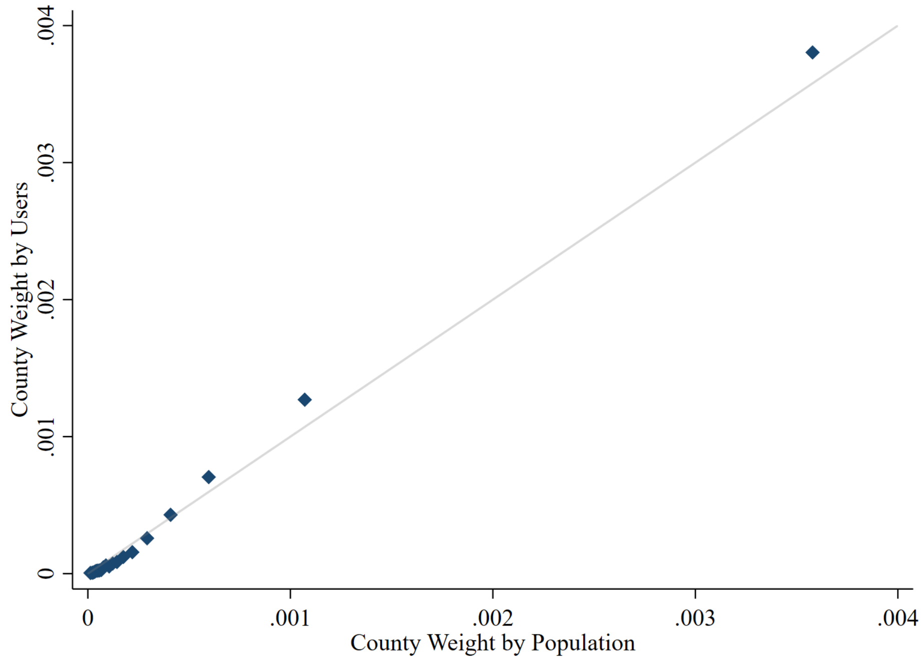
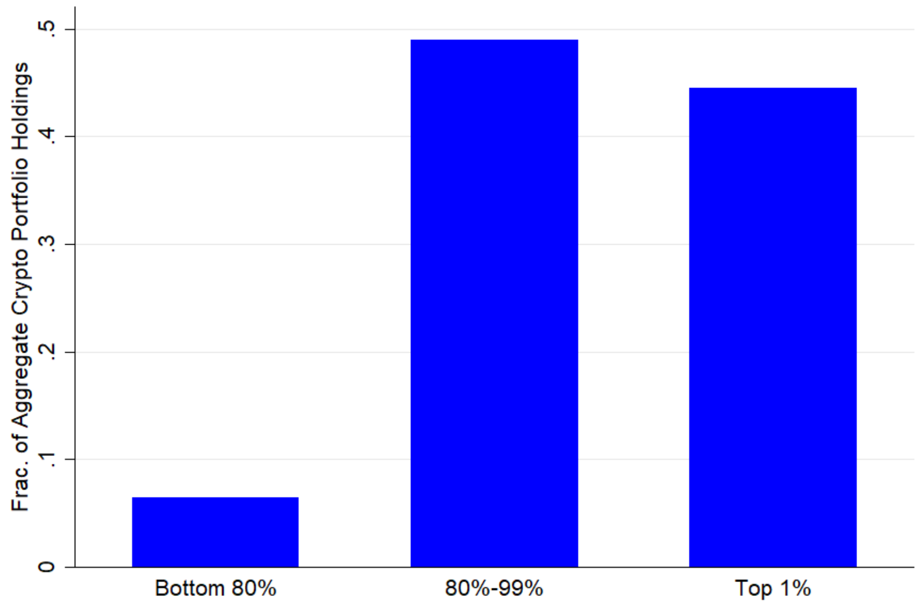


Figure A.1. County Weights by Population vs. Transaction Users. This figure shows a binscatter of county weights based on county population vs county weights based on the number of households in our transaction database.



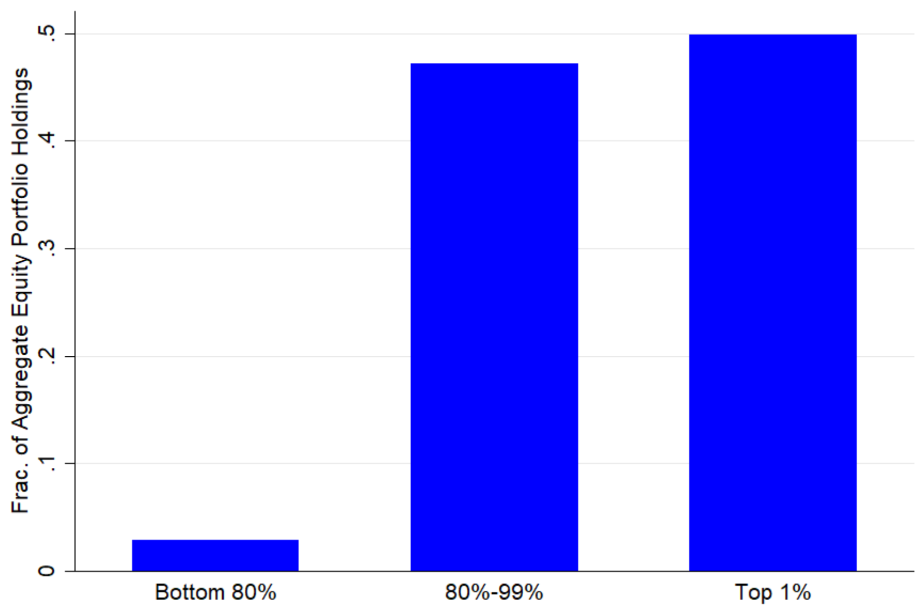
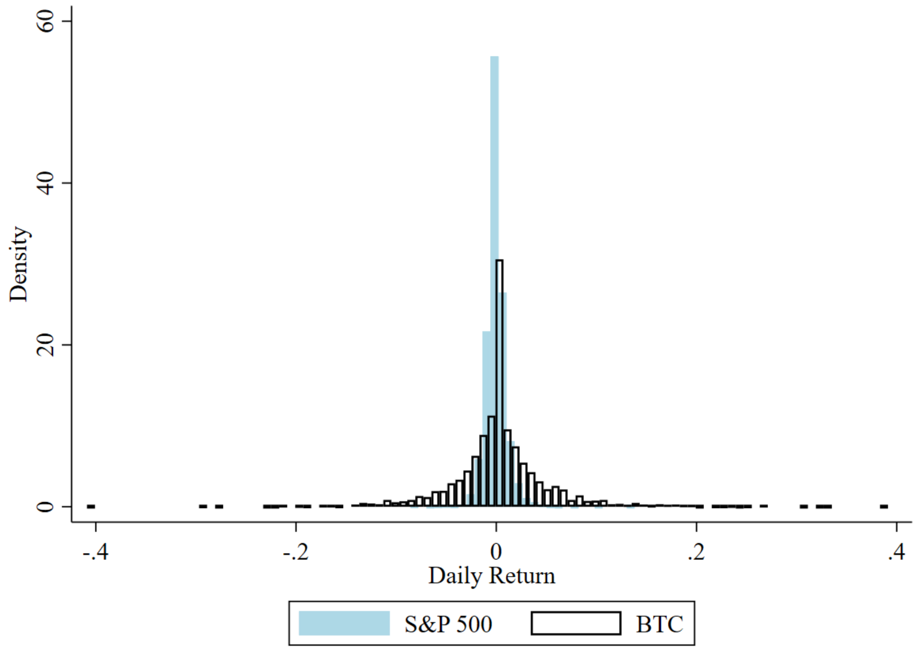


Figure A.2. Distribution of Investment Wealth. These figures show the distribution of investment wealth. The top figure presents the distribution of total crypto portfolio values as of December 2021 for our sample of crypto users. The bottom figure shows the distribution of equity portfolio values for U.S. households based on the 2016 Survey of Consumer Finances (SCF).



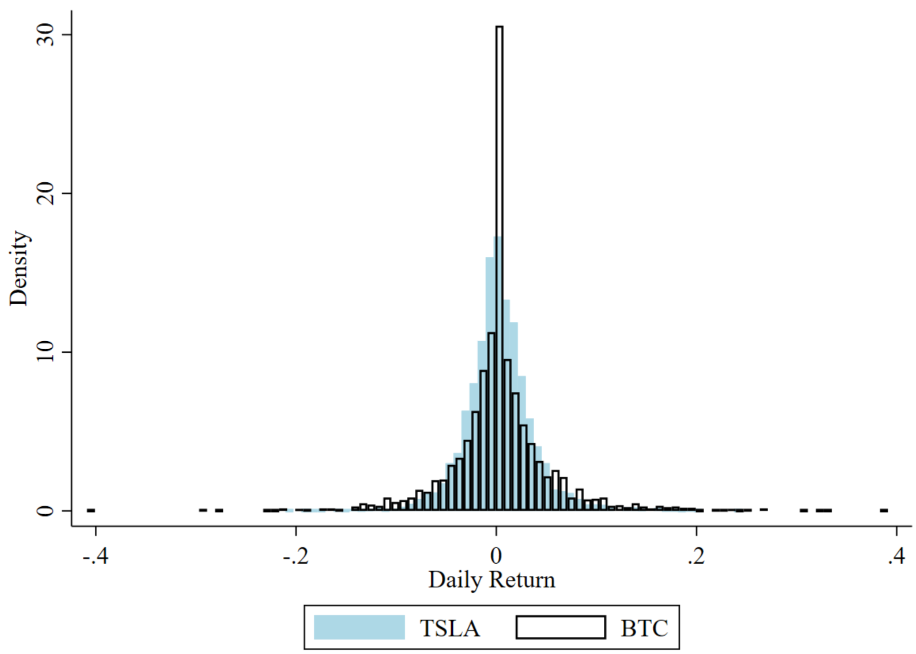


Figure A.3. Distribution of Daily Returns. These figures show the distribution of Bitcoin and equity daily returns between 2014 and 2022. The top figure presents the distribution of daily Bitcoin returns and the S&P 500. The second one shows Bitcoin returns and Tesla returns.

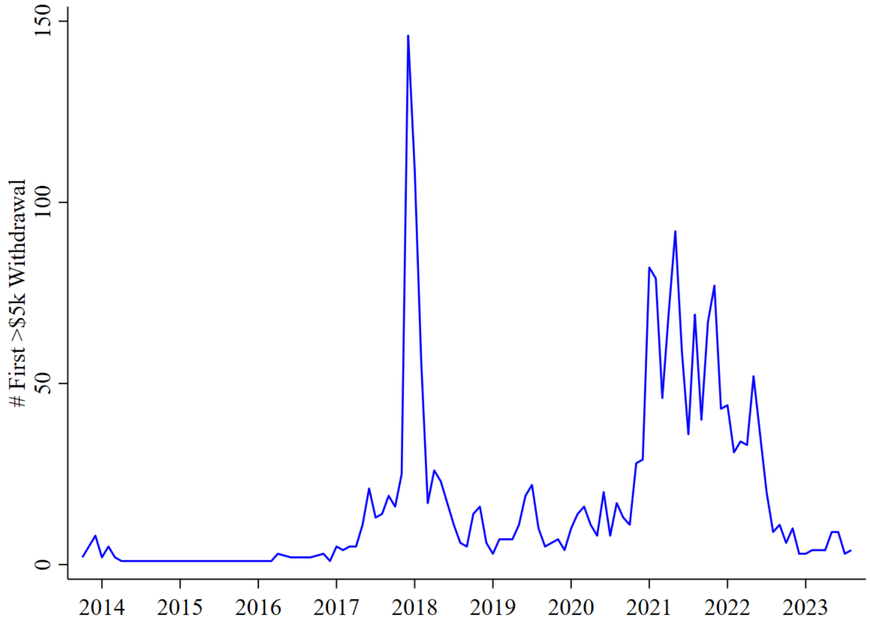


Figure A.4. Large Crypto Withdrawals. This figure shows the number of first-time large crypto withdrawals (greater than $5,000) each month for our sample of crypto users. We use this sample in our withdrawal event study reported in Tables 6 and 7.

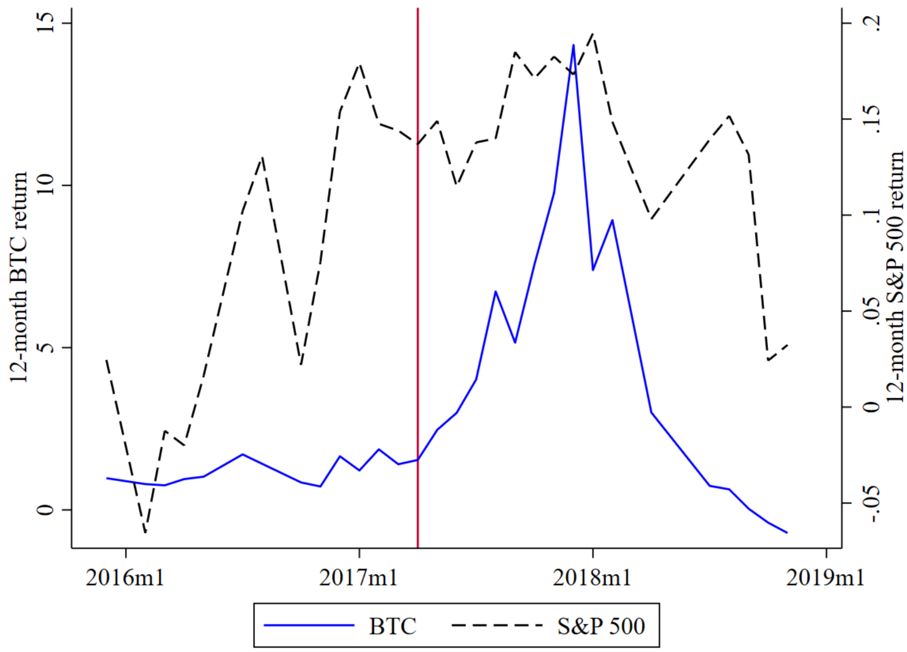


Figure A.5. Bitcoin and S&P 500 Rolling 12-month Returns. This figure shows the 12-month holding period returns each month for holding Bitcoin and the S&P 500. The figure plots the returns on separate axes, with Bitcoin returns on the left axis. The red line in the figures indicates the pre- and post-periods used in our difference-in-differences analysis reported in Table 8, which we define based on the beginning of the Bitcoin price run-up.

Figure A.6. Equity Investment Withdrawals around Bitcoin Run-up by Crypto Wealth. This figure shows county-level per capita withdrawals from traditional brokerages each month separately for high and low crypto wealth counties. High (low) crypto wealth counties are defined based on the top (bottom) tercile of per capita crypto wealth as of December 2016. Investment withdrawals are identified as credits to the user's account from retail trading platforms such as Fidelity, Charles Schwabb, Robinhood, Acorns, etc. The red line in the figure indicates the pre- and post-periods used in our difference-in-differences analysis reported in Table 8, which we define based on the beginning of the Bitcoin price run-up.

Table A.1

Crypto Gains and Investment

This table tests the sensitivity of crypto and equity investments to gains in crypto wealth. The primary independent variable is a household's average quarterly change in crypto wealth defined in Equation 2. The dependent variable in column (1) is the sum of a household's crypto deposits in the quarter. In column (2) the dependent variable is the sum of deposits made in traditional brokerages in the quarter. Finally, in column (3) the dependent variable is the sum of crypto withdrawals in the quarter. All regressions include a control for the household's income from the previous quarter, as well as household and state-by-quarter fixed effects. Columns (1) and (2) include both crypto and non-crypto investors; crypto gains are defined as zero for non-crypto investors. Column (3) uses a subsample restricted to crypto investors. *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Total Quarterly Crypto Deposits	Total Quarterly Investment Deposits	Total Quarterly Crypto Withdrawals
	OLS	OLS	OLS
	(1)	(2)	(3)
Avg. Quarterly Crypto Gains	0.0906***	0.0561***	0.177***
	(7.81)	(2.97)	(5.65)
Lagged Crypto Deposits	0.278***		0.0434***
	(9.05)		(3.62)
Lagged Investment Deposits		0.0279***	
		(2.94)	
Lagged Income Control	X	X	X
Household FE	X	X	X
State × Quarter FE	X	X	X
Observations	4,312,861	4,312,861	758,310
Adjusted R^2	0.151	0.079	0.045

Table A.2

Crypto Gains and Total Spending Including Covid Period

This table shows the marginal propensity to consume (MPC) out of crypto wealth. The dependent variable is the household's total spending in the quarter. *Avg. Quarterly Crypto Gains* is the average quarterly change in the household's crypto wealth over the prior year defined in Equation 2. The sample includes both crypto investors and non-crypto investors; crypto gains are equal to zero for non-crypto investors. *Covid* is an indicator equal to 1 for observations in 2020 or 2021. *Avg. Quarterly Investment Gains* is the average quarterly change in the household's brokerage account wealth over the prior year, calculated analogously to Equation 2. All regressions include a control for the household's income from the previous quarter, as well as household and state-by-quarter fixed effects. Columns (3) and (4) are estimated using two-stage least squares (2SLS) where passive crypto gains, defined in Equation 4, are used as an instrument for crypto gains, and passive investment gains, defined analogously, are used as an instrument for investment gains. Passive gains are calculated as what the household would have received if their portfolio had been fixed 12 months prior and had experienced the value-weighted returns of Bitcoin and Ethereum (or S&P 500 with respect to passive investment gains). The interactions with gains and the Covid indicator are instrumented using the relevant measure of passive gains interacted with the Covid indicator. The Kleibergen-Paap rk Wald F statistic is reported for all 2SLS specifications. t-statistics in parentheses are heteroskedasticity-robust and clustered at the household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Total Quarterly Spending			
	OLS	OLS	2SLS	2SLS
	(1)	(2)	(3)	(4)
Avg. Quarterly Crypto Gains	0.0146	0.107***	0.0825***	
	(1.42)	(5.66)	(4.22)	
Avg. Quarterly Crypto Gains × Covid Indicator		-0.149***	-0.135***	
		(-5.75)	(-4.98)	
Avg. Quarterly Investment Gains				0.0804***
				(8.38)
Avg. Quarterly Investment Gains × Covid Indicator				-0.115***
				(-10.83)
Lagged Income Control	X	X	X	X
Household FE	X	X	X	X
State × Quarter FE	X	X	X	X
Observations	4,312,861	4,312,861	4,312,861	4,312,861
Adjusted R^2	0.676	0.676	0.084	0.084
Weak ID KP F Stat			5,814	7,027

Table A.3

Crypto Gains and Total Spending with Broader Coin Index

This table shows the marginal propensity to consume (MPC) out of crypto wealth. The dependent variable is the household's total spending in the quarter. The sample covers years 2015–2023, but omits observations that occur during the Covid period, defined as 2020–2021. *Avg. Quarterly Crypto Gains (Index)* is the average quarterly change in crypto wealth over the prior year defined in Equation 2 where the crypto index includes the 17 largest coins weighted by transaction volume. *Post-Covid* is an indicator equal to 1 for observations in 2022 or 2023. All regressions include a control for the household's income from the previous quarter, as well as household and state-by-quarter fixed effects. Columns (2) and (3) are estimated using two-stage least squares (2SLS) where passive crypto gains, defined in Equation 4, are used as an instrument for crypto gains. Passive gains are calculated as what the household would have received if their portfolio had been fixed 12 months prior and had experienced the value-weighted returns of the 17 coin index. In column (3), we instrument for the interaction of crypto gains with the post-Covid indicator using the interaction of passive crypto gains and the post-Covid indicator. The Kleibergen-Paap rk Wald F statistic is reported for all 2SLS specifications. *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Total Quarterly Spending		
	OLS	2SLS	2SLS
	(1)	(2)	(3)
Avg. Quarterly Crypto Gains (Index)	0.100***	0.0667***	0.0733***
	(5.55)	(3.50)	(2.83)
Avg. Quarterly Crypto Gains (Index)			-0.0115
× Post-Covid Indicator			(-0.32)
Lagged Income Control	X	X	X
Household FE	X	X	X
State × Quarter FE	X	X	X
Observations	3,285,069	3,285,069	3,285,069
Adjusted R^2	0.689	0.082	0.082
Weak ID KP F Stat		11,409	3,161

Table A.4

MPC Split by Income Tercile

This table shows consumption sensitivity to crypto and traditional brokerage wealth by income terciles. The dependent variable is the household's total spending in the quarter. *Avg. Quarterly Crypto Gains* is the average quarterly change in the household's crypto wealth over the prior year defined in Equation 2. The sample includes both crypto investors and non-crypto investors excluding the Covid period (i.e., years 2020 and 2021); crypto gains are equal to zero for non-crypto investors and investment gains are zero for households that do not invest in traditional brokerages. All regressions include a control for the household's income from the previous quarter, as well as household and state-by-quarter fixed effects. The regressions are estimated using two-stage least squares (2SLS) where passive crypto gains, defined in Equation 4, are used as an instrument for crypto gains in columns (1)–(3) and passive investment gains, defined analogously, are used as an instrument for investment gains in columns (4)–(6). Passive gains are calculated as what the household would have received if their crypto (traditional) portfolio had been fixed 12 months prior and had experienced the value-weighted returns of Bitcoin and Ethereum (S&P 500). Columns (1), (2), (4), and (5) are restricted to the subsample of households below and above median income as indicated in the table. Households are assigned to income percentiles based on the full sample distribution in the first quarter that the household appears in the data. Columns (3) and (6) are estimated using the full sample of households and include indicators for households with above median income interacted with portfolio gains. We instrument for these interactions with the relevant measure of passive gains interacted with the high income indicator. The Kleibergen-Paap rk Wald F statistic is reported for all 2SLS specifications. *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Total Quarterly Spending			Total Quarterly Spending		
	2SLS	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)	(6)
Avg. Quarterly Crypto Gains	0.0638***	0.0970***	0.0600***			
	(2.75)	(3.15)	(2.58)			
Avg. Quarterly Crypto Gains × High Income			0.0372			
			(0.97)			
Avg. Quarterly Investment Gains				0.0988***	0.0431***	0.0999***
				(5.04)	(3.70)	(5.11)
Avg. Quarterly Investment Gains × High Income						-0.0570**
						(-2.51)
Standard FEs and Controls	X	X	X	X	X	X
Sample	Low Income	High Income	All Households	Low Income	High Income	All Households
Observations	1,930,089	1,344,549	3,274,638	1,930,089	1,344,549	3,274,638
Adjusted R^2	0.121	0.063	0.081	0.120	0.062	0.080
Weak ID KP F Stat	5,711	5,865	2,933	2,190	9,580	1,094

Table A.5

Propensity to Consume out of Crypto Wealth

This table shows the marginal propensity to consume (MPC) out of crypto wealth for various spending categories. *Avg. Quarterly Crypto Gains* is the average quarterly change in crypto wealth over the prior year defined in Equation 2. All regressions include a control for the household's income from the previous quarter, as well as household and state-by-quarter fixed effects. The regressions are estimated using two-stage least squares (2SLS) where passive crypto gains, defined in Equation 4, are used as an instrument for crypto gains. Passive gains are calculated as what the household would have received if their portfolio had been fixed 12 months prior and had experienced the value-weighted returns of Bitcoin and Ethereum. *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Quarterly Spending				
	Total Spending	Auto	Cable/Telecom	Cash/Check	Charity
	2SLS	2SLS	2SLS	2SLS	2SLS
	(1)	(2)	(3)	(4)	(5)
Avg. Quarterly Crypto Gains	0.0879***	0.00528***	-0.00250***	0.0412***	0.000297
	(4.43)	(3.54)	(-3.55)	(3.02)	(0.60)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
State × Quarter FE	X	X	X	X	X
Sample	Non-Covid	Non-Covid	Non-Covid	Non-Covid	Non-Covid
Observations	3,274,658	3,274,658	3,274,658	3,274,658	3,274,658
Adjusted R^2	0.082	0.011	0.019	0.021	0.001

	Quarterly Spending				
	Education	Entertain/Travel	General Merch.	Groceries	Insurance
	2SLS	2SLS	2SLS	2SLS	2SLS
	(6)	(7)	(8)	(9)	(10)
Avg. Quarterly Crypto Gains	0.00245	0.00701***	0.0200***	0.0106***	-0.00274**
	(1.23)	(2.75)	(4.57)	(6.74)	(-2.39)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
State × Quarter FE	X	X	X	X	X
Sample	Non-Covid	Non-Covid	Non-Covid	Non-Covid	Non-Covid
Observations	3,274,658	3,274,658	3,274,658	3,274,658	3,274,658
Adjusted R^2	0.000	0.013	0.038	0.022	0.008

	Quarterly Spending				
	Medical	Mortgage	Rent	Restaurants	Utilities
	2SLS	2SLS	2SLS	2SLS	2SLS
	(11)	(12)	(13)	(14)	(15)
Avg. Quarterly Crypto Gains	0.00192***	-0.00366	0.00178	0.0108***	-0.00108
	(2.86)	(-0.74)	(0.99)	(5.94)	(-1.09)
Lagged Income Control	X	X	X	X	X
Household FE	X	X	X	X	X
State × Quarter FE	X	X	X	X	X
Sample	Non-Covid	Non-Covid	Non-Covid	Non-Covid	Non-Covid
Observations	3,274,658	3,274,658	3,274,658	3,274,658	3,274,658
Adjusted R^2	0.006	0.015	0.001	0.027	0.014

Table A.6

Equity Withdrawals and Transition into Homeownership

This table presents event study regressions similar to those of Table 6 but focusing on mortgage spending and new home ownership. Columns (1) and (3) define an event as a first traditional investment brokerage withdrawal in excess of $5,000 and columns (2) and (4) define an event as a first withdrawal in excess of $10,000. The dependent variable in Columns (1) and (2) is monthly mortgage spending. In Columns (3) and (4), *New Homeowner* is an indicator variable equal to 1 if the household has had mortgage spending less than $100 over the previous 6 months and more than $2,500 over then following 6 months. All regressions include a control for the household's income from the previous month, as well as household and year fixed effects. *t*-statistics in parentheses are heteroskedasticity-robust and clustered at the household level. ***, **, and * indicate statistical significance at the 1%, 5%, and 10% levels, respectively.

	Monthly Mortgage Spending, Annualized		New Homeowner	
	OLS	OLS	OLS	OLS
	(1)	(2)	(3)	(4)
Post First Equity Withdrawal >$5,000	760.4***		0.0318***	
	(9.05)		(11.39)	
Post First Equity Withdrawal >$10,000		921.7***		0.0311***
		(8.30)		(8.99)
Lagged Income Control	X	X	X	X
Household FE	X	X	X	X
Year FE	X	X	X	X
Observations	256,683	170,115	256,683	170,115
Adjusted R^2	0.687	0.685	0.219	0.218